WHY TIME AWAY FROM PRACTICE IMPROVES PERFORMANCE: A TEST OF THREE MEMORY-BASED EXPLANATIONS

by

Linda Jean Sorensen

A dissertation submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Department of Educational Psychology

The University of Utah

August 2014

The University of Utah Graduate School

STATEMENT OF DISSERTATION APPROVAL

The dissertation of **Linda Jean Sorensen**

has been approved by the following supervisory committee members:

Dan Woltz	, Chair	**4/24/2014** Date Approved
Michael Gardner	, Member	**4/24/2014** Date Approved
Anne Cook	, Member	**4/24/2014** Date Approved
John Kircher	, Member	**4/24/2014** Date Approved
Frances Friedrich	, Member	**4/24/2014** Date Approved

and by **Anne Cook** , Chair/Dean of

the Department/College/School of **Educational Psychology**

and by David B. Kieda, Dean of The Graduate School.

ABSTRACT

Prior evidence from several research areas suggests that performance improvements can accrue during intervals that preclude further practice of a procedural skill; however, the mechanism underlying this improvement is unclear. In order to test competing explanations for such improvement, the author investigated the effects of varying the cognitive demands of a secondary task interpolated into a course of cognitive skill practice. The moderately complex skill task that was used presented electrical circuitry operations (logic gates) and their corresponding rules, which participants learned first through declarative instruction and thereafter through multiple blocks of procedural practice. The interpolated task was either a cognitively demanding working memory (WM) test or a noncognitively demanding period spent listening to binaural alpha-wave beats over headphones. Three theory-based explanations for skill improvement during the interpolated task, or *gap facilitation*, were tested: memory consolidation, release from proactive interference (PI), and mental rest. Each explanation makes unique predictions regarding parameters of a power function used to describe the trajectory of each participant's skill performance before and after the interpolated tasks. Evidence favored release from PI as being responsible for the observed gap facilitation effects. Findings are interpreted with respect to learning theory that predicts performance decline with time away from practice and in light of prior explanations of evidence to the contrary.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

In the course of practicing a computerized cognitive skill, participants in a previous experiment in my research encountered a midsession break filled by an unrelated associative task. After the break, these participants exhibited immediate improvement in performance of the original skill, an outcome unpredicted by prominent theories of skill acquisition. Extensive practice of a skill typically produces systematic performance changes evidenced by steady reductions in both response time (RT) and errors (Newell & Rosenbloom, 1981), while time away from practice (i.e., *offline*) results in a temporary decrement in performance attributable to a loss of strength in inactive memory elements (Anderson, Fincham, & Douglass, 1999). This loss of memory strength is manifested in longer RT and/or a drop in accuracy level and appears as a perceptible scallop in the negatively accelerated learning curve after resumption of practice. As such, the observed short-term skill improvement following a gap injected into a practice session will be dubbed *gap facilitation* and demands an explanation.

Although gap facilitation is inconsistent with cognitive theories of skill acquisition, it is not unprecedented; at least three plausible explanations for the observed effect exist. The first explanation is memory consolidation. During the gap period in the previous experiment (hereinafter referred to as the *pilot*), participants engaged in an implicit associative learning task. The nontaxing, noninterfering nature of the interpolated activity could have allowed memory representations of the declarative rules and initial procedural compilations of the previously practiced skill to freely consolidate. The result of this offline stabilization of newly acquired skill representations would be behaviorally evidenced through the dependent measures.

As a second explanation, it is possible that improvement in performance immediately following the break was due to a release from proactive interference (PI) that had built up during the initial skill practice blocks. As participants rapidly and repeatedly solved three-part sequences of highly overlapping problems, both the increased activation and enhanced memory strength for a just-solved item could have interfered with retrieval of the memory trace for the next item. Such interfering influences could have caused a gradual slowing of improvement in RT in the practice blocks, but it presumably would have dissipated during the interpolated task.

Mental rest is the third plausible explanation for unpredicted gap facilitation following the interpolated task in the pilot. Task fatigue has been found to build quickly under conditions of sustained focus and rapidly repeating stimuli such as existed in that experiment (Gunzelmann, Moore, Gluck, Van Dongen, & Dinges, 2011). Perhaps, after switching away for a short time from the attentional demands of their cognitive skill practice and engaging in a simpler task, participants found their stores of energy and motivation replenished. Upon resuming procedural practice, their immediately enhanced performance evidenced the benefit of cognitive rest.

These potential explanations for facilitated performance after a gap are neither mutually exclusive nor exhaustive. Any one of the phenomena, or a combination of them, could be responsible for the observed skill improvement. Despite the likely complexity of the underlying cause, an understanding of this phenomenon is worth pursuing because of potentially important implications both for theory and application. The findings could contribute to theory because prominent memory models of skill learning do not predict gap facilitation. Moreover, any training manipulation that improves performance, especially if it is relatively simple to implement, has potential application to the design of real world skill training. The purpose of this research, then, is to better understand the underlying cognitive processes that might precipitate—and sustain—gap facilitation.

CHAPTER 2

LITERATURE REVIEW

This dissertation study required participants to acquire a cognitive skill through procedural practice in order that the effects on performance of diverse interpolated tasks could be investigated. As such, this literature review consists of two parts. First, I review pertinent literature related to cognitive skill acquisition, including the phases of learning hypothesized to enable skilled performance, prominent theories of how procedural knowledge is represented in memory, and the power law of practice. Second, I explore three cognitive constructs that could be responsible for anticipated gap facilitation effects: memory consolidation, release from PI, and mental rest.

Cognitive Skill Learning

Skill in general has been conceptualized as "goal-directed, well-organized behavior that is acquired through practice and performed with economy of effort" (Proctor & Dutta, 1995, p. 18). Cognitive skill, the type under investigation in this experiment, involves symbolic goals and is presumed acquired when an individual demonstrates the ability to solve problems or perform tasks in the intellectual domain (VanLehn, 1996). This type of skill is usually distinguished from skill in the perceptual-motor domain, in which goals such as playing the piano or hitting a golf ball are nonsymbolic (Rosenbaum, Carlson, & Gilmore, 2001). Despite the obvious differences in their expression, however, cognitive and perceptual-motor skills are psychologically more alike than different, as least in their acquisition (Bartlett, 1958; Rosenbaum et al., 2001). Newell (1991) went so far as to assert that traditional distinctions between skill categories are essentially matters of heuristic convenience. As a result, principles that hold in one domain are presumed to hold in the other for the present purposes, unless otherwise noted.

Another distinction typically drawn in discussions of skill acquisition is between declarative knowledge and procedural knowledge. Declarative knowledge reflects factual, verbalizable information, while procedural knowledge reflects a set of skills a person is capable of performing (Proctor & Dutta, 1995). Unlike the debatable differences between cognitive and perceptual-motor skill acquisition, the declarative-procedural knowledge distinction is widely accepted and vital because most, if not all, prominent models of skill acquisition posit distinct memory mechanisms within each. Typically, learners are understood to progress from accessing slow, WM-intensive representations (i.e., declarative knowledge) to employing fast, nonattention-demanding representations (i.e., procedural knowledge) through extensive practice (e.g., Anderson, 1982, 1983; Fitts & Posner, 1967; Logan, 1988; Newell & Rosenbloom, 1981).

Finally, cognitive skills are presumed to exist along a continuum from simple to complex. Simple skills, such as perceptual and classification tasks, consist of few basic components and can be developed quickly under conditions of relatively modest practice; by contrast, complex skills, such as those used to solve complicated mathematics problems, require integration of multiple components and many repetitions before expertise can be developed (Johnson, 2013). In a seven-component conceptualization of task difficulty, Gilbert, Bird, Frith, and Burgess (2012) contrast more- and less-demanding tasks based, in part, on the requisite executive function involvement. More difficult tasks are defined as those requiring the transformation of internal representations germane to task performance, in a manner independent of concurrent sensory input, while simpler tasks may be executed based on comparatively direct stimulus-response associations. As such, the level of complexity of the cognitive skill used in this experiment may be envisaged as somewhere in the middle of the spectrum: simple enough that participants can proceed through the essential phases of learning in the allotted time (1 hr), but complex enough to allow for investigation of changes in knowledge representation following a potentially impactful interpolated task.

Phases of Learning

In experimental settings, determining a subject's capability in a particular skill is based in large part upon the level of fluency (i.e., expertise) the person has gained in an activity like mirror tracing or puzzle solving within a given practice period (Rosenbloom, Laird, & Newell, 1993). Expertise develops gradually, but participants have been described as passing through three phases of learning: *cognitive*, *associative*, and *autonomous* (Fitts, 1964).

The first learning phase is called cognitive because it describes the stage when declarative processes are employed by the learner to explicitly understand a novel task and what is required to perform it correctly. Working memory and attentional requirements are initially high, and performance feedback is generally provided. The associative phase unfolds as inputs and appropriate actions are adjoined more directly, thus lessening the need for verbal mediation (Proctor & Dutta, 1995). Errors, while still present in the associative phase, are rapidly decreasing, as is the time required to perform the action. The final, autonomous phase evidences procedural learning and is marked by the lessening of attentional requirements, a reduction of influence from outside interference, and cognitive processes and responses that appear to be triggered automatically rather than deliberately.

This description of the phases of learning is included here because participants in this experiment, during a single experimental session, transformed from novices to skilled performers of a moderately complex cognitive task by progressing sequentially and systematically through each phase. It was crucial that participants developed at least a moderate level of skill at the task—as evidenced by decreasing individual RT and high levels of accuracy—in order that gap effects of any kind resulting from the break were detectable.

Knowledge Representations in Selected Theories of Skill Acquisition

Several prominent theories of skill acquisition describe memory mechanisms that enable the development of expertise through practice. Arguably the most comprehensive model for learning—and the one that will be adopted for the present discussion—is John R. Anderson's Adaptive Control of Thought (ACT) framework (e.g., 1983, 1993; Anderson et al., 2004). This production-system architecture envisions cognitive skill as composed of production rules organized around sets of goals. The ACT model has, across all its modifications, maintained a distinction between declarative and procedural knowledge. Declarative knowledge, roughly corresponding to Fitts' (1964) cognitive phase, is flexible; it takes the form of *chunks* and represents factual, mostly reportable information. Procedural knowledge, contained in *productions* which are efficient for specific usage, is only manifested by performance, analogous to the associative and are encoded, then strengthened with repeated use.

Newell and Rosenbloom's *Chunking Theory of Learning* (1987) is based on similar underlying principles as those incorporated in ACT. Separate pieces of general knowledge of the environment are acquired and organized into basic structures also referred to as chunks. Chunks vary as to composition, size, and function (e.g., primitive, internal-processing, perceptual, motor, etc.), but all are capable of coalescing into higher-level chunks. Depending upon the structure of the task environment, it is these higher-level chunks that are conducive to streamlined (faster) processing with practice.

In a different conceptualization of skill acquisition, Logan's (1988) instance theory of automaticity envisions skilled performance as being associated with a specific type of cognitive processing. According to instance theory, every knowledge representation underlying performance is a separable *instance* from practice which links a specific stimulus to a specific response. New practice events are initially processed using a general algorithm, but with each repetition of the associated process, a separate memory trace is laid down. As the number of traces associated with a particular problem type grows, memory strength manifests as instance retrieval rather than a re-instantiation of the algorithm. Automaticity, as evidenced by speeded processing, is deemed achieved when performance is based fully on instance memory retrieval, regardless of the number of prior repetitions. In essence, a learning mechanism develops which transitions slower, rule-based processing into faster, memory-based processing—the observable consequence of which is rapid and relatively effortless performance.

<u>The power law of practice</u>. Most theories of skill acquisition predict that the time needed to accomplish a task decreases systematically in proportion to the number of trials

raised to some power (Van Lehn, 1996), not that performance will improve while the learner is offline. Sheer amount of practice has been shown to accurately account for performance time improvements in a variety of skills, from rolling cigars to solving geometry proofs (Newell & Rosenbloom, 1981). Observed improvements in skill are accurately fitted by general power functions of the form:

$$T = a(N + E)^{-b}, \quad [1]$$

where T is performance time at a given practice event, a is initial performance time, N is the number of practice events, E is the number of trials constituting prior experience ($E \geq 0$), and b is the learning rate ($0 \leq b < 1$). Given the nearly universal fit of this function to both cognitive and motor skill learning data, Newell and Rosenbloom declared it the *power law of practice.* Even under Logan's (1988) instance theory of automaticity, as skill performance transitions from algorithm-based retrieval to memory-based retrieval, it is presumed to be governed by the power law.

Memory mechanisms that account for the reliable fit of power functions to human performance data are integral to theories of skill acquisition. According to the Adaptive Control of Thought—Rational (ACT-R; Anderson, 1993) framework adopted here, the strength of a memory representation is a function of the number of learning repetitions, the time elapsed since the last repetition, and a forgetting rate. With extensive practice, knowledge representations of to-be-learned stimuli evolve from a slow, declarative format into a fast, procedural format which can be more speedily accessed. Improvement is steady and systematic and could theoretically continue without an asymptote if not for physical limitations. Of primary importance, no theory that explains power law learning predicts that a gap during practice (i.e., a time lag between sets of practice events) would result in improved performance. On the contrary, a gap in practice necessarily reduces memory strength as a function of the decay rate, which in turn increases performance time.

Strength decay. Performance degradation over time away from practice is an outward manifestation of forgetting (Anderson & Schunn, 2000), which is thought by some to follow a power function just as skill acquisition does (Rubin & Wenzel, 1996). If the gap effect observed after an interpolated task is a decrement in skill performance rather than an improvement, strength decay will be a potential explanation.

Ebbinghaus (1885/1964) speculated that forgetting occurs as a function of time, a notion that evolved into decay theory in general, and the law of disuse in particular (Thorndike, 1905). Gates (1930) concurred, asserting that trained mechanisms passively weaken when left inactive. However, time is rarely spent in a vacuum, a necessary condition were decay alone to be conclusively accepted as the root of forgetting (Dewar, Cowan, & Della Sala, 2007). Indeed, cognitive neuroscientists have recently observed that even when individuals are left undisturbed, their minds are not inactive. The human brain’s default mode network is actively engaged in problem solving, reflecting on the past, imagining future events, and considering others' thoughts and feelings, for example (Buckner, Andrews-Hanna, & Schacter, 2008). As such, researchers have long recognized that interpolated events and altered stimulating conditions are the key influences in the production of forgetting (McGeoch, 1932). The detrimental force acting on memory under such circumstances, McGeoch argued, was interference, not decay.

If performance ability of a skill declines because a learner is offline—whether due to disuse, some type of interference, or a combination of the two—the resultant upswing (i.e., worsening) in the RT learning curve could be because the production strength for the newly learned information weakened during the gap in practice. Anderson and colleagues (1999) proposed this and conducted a series of cognitive skill acquisition experiments to investigate the utility of a strength accumulation equation designed to predict both power law practice and power law retention over various lengths of time (up to 400 days). In five experiments they consistently noted a spike in RT as participants returned to the learning task, regardless of the length of retention interval. Adopting a phrase from past researchers (e.g., Adams, 1961; Postman, 1961; Schmidt, 1988), they described the initial slowing after a break as a *warm-up decrement*. Warm-up decrements disappeared after only a few trials as practice resumed, however, because the delay increments, though large, are rapidly added to the base strength. With enough continuous practice, absolute skill level would approximate the proficiency level attained if no break were interpolated. Of importance here, the ACT-R theory predicted a decrement in performance due to forgetting during time away from practice, rather than a performance benefit.

Influences Contributing to Gap Effects during Skill Learning

Skill does not develop instantaneously but rather is acquired over time as a function of some amount—usually a great deal—of practice. Indeed, the power law of practice virtually guarantees performance improvement of the repeated behavior as long as there is consistency in task demands and practice steadily occurs (within physical limits). Unfortunately, faculties necessary for continuous effort (e.g., stamina, attention, muscle strength, motivation) are unstable and limited, requiring replenishment at regular intervals. Periods of nonpractice (*breaks, gaps*, or time spent *offline*) are inevitable, therefore, and standard fare in studies of skill acquisition. This is especially true during attainment of complex motor skills, when demands on fatigue-prone physical abilities are high. Constraints also operate on cognitive skill acquisition, however, where mental fatigue can reduce activation, decrease motivation, and ultimately stunt task performance (Lorist & Faber, 2011). Fortunately, interpolating a gap into a course of skill practice does not always deter learning, though the power law of practice would predict otherwise. In some circumstances, performance actually improves after a break. Subsequent sections of this review describe evidence and theory related to three cognitive constructs associated with gap facilitation effects; specifically, memory consolidation, release from PI, and mental rest.

Memory Consolidation

Consolidation is defined as a hypothetical process during which a memory item stabilizes into a long-term form (Dudai, 2012). The first suggestion that memories consolidate following learning emerged from recall experiments conducted by German psychologists Muller and Pilzecker (1900). This teacher-student duo is credited with initiating scientific usage of the term *konsolidierung*, or consolidation. Their subjects, who had studied lists of nonsense syllables, often lamented that repetitions of the trigrams subsequently entered their minds unbidden. This led to the hypothesis, borrowed from psychopathology, that newly formed memories *perseverate*, or continue to be processed apart from the experimental task, before achieving long-term storage. Muller and Pilzecker went so far as to speculate, quite presciently, that perseveration was the result of "transitive activity in the brain that encoded associative memory" (p. 78).

Laboratory evidence has expanded on Muller and Pilzecker's (1900) findings over the past century, but often without a consensus of opinion among researchers as to conclusions drawn. For example, memory consolidation was presented by Peterson (1966) and Landauer (1969) as an explanation for increased retrievability of a memory trace over a time, but this explanation for short-term spacing effects was frowned upon during the 1970s when the zeitgeist favored voluntary control processes; consolidation is presumed to occur involuntarily (Hintzman, 1974; Melton, 1969). More recently, however, accumulating neural evidence suggests that the brain continues to process information even when practice stops, with changes taking place that serve to both strengthen and modify newly learned skill (e.g., Robertson, Pascual-Leone, & Miall, 2004). Memories of all kinds undergo postencoding stabilization processes through which they become more resistant to interference (Stickgold, 2005; Walker, 2005). Memory for just-learned material is often enhanced during sleep (Jenkins & Dallenbach, 1924), and certain psychopharmacological agents with sedative properties (e.g., alcohol, benzodiazepines) have been found to improve memory for information studied immediately prior to their consumption (Wixted, 2004).

With regard to specific skill types, perceptual-motor performance has been found, under at least some circumstances, to improve during a break between training and test (Marshall & Born, 2007). This finding has been taken to imply that representations associated with proceduralized skill are not fully formed at acquisition (Walker, 2005). Walker proposed that memory formation occurs during at least two stages of consolidation: stabilization, believed to occur during wake, and enhancement, believed to occur during sleep. In a study investigating the role of the primary motor cortex in postencoding stabilization processes, brain researchers (Muellbacher et al., 2002) trained subjects in a ballistic pinch test (i.e., accelerated, forceful index finger-thumb pinches to the beat of a metronome). Following a 15-min retention interval during which they rested, Group 1 performed as well at test as they had before the break. Rather than rest, Group 2 immediately underwent 15 min of repetitive transcranial magnetic stimulation (rTMS), an intervention known to disrupt local neuronal activity. When tested, Group 2 had regressed to prepractice levels. Group 3 wakefully rested for 6 hr following training, then underwent rTMS. These subjects evidenced no interference effect from rTMS when tested immediately after the stimulations, exhibiting the same performance levels they had achieved at the end of the training session. This study suggests that motor memory is time dependent (as opposed to sleep dependent), rapidly transforming from a labile to a stable state. In the absence of immediate interference, ability level of this motor skill maintained without further practice.

In an oft-cited perceptual learning study, Karni and Sagi (1993) investigated the role of attention in detecting, versus discriminating, the visual orientation of embedded objects. These researchers required participants to determine, at ever-decreasing stimulus-to-mask onset asynchronies, the directional orientation of a tiny, briefly presented (10 ms) target array situated within a sea of similar, differently oriented stimuli. A consistent pattern of learning emerged across 19 training sessions, but the gains came between, not within, sessions spaced 1-3 days apart. According to Karni and Sagi, “Where perception completely fails on the initial session, there is > 90% correct discrimination on the following day” (p. 250).

To further scrutinize the time course of the observed perceptual skill improvement, Karni and Sagi (1993) repeated the test procedure in probe sessions which varied in number (1-3) and schedule (from 20 min to 10 hr posttraining) across the 9 participants. For example, 1 subject was probed three times, on a 20 min-2 hr-6 hr schedule, while another was tested once, at the 1-hr point. All were retested between 20-30 hr after initial training. No increase in visual discrimination skill was observed in any participant between 20 min and 8 hr after cessation of training (the *latent* phase). At the 8-hr point, 2 participants did show improvement, and on the following day, all participants evidenced large skill gains. Importantly, the additional practice opportunities experienced by some did not induce larger long-term gains, suggesting that training which occurred during the latent phase was superfluous. Rather, learning was deemed driven by sensory capability acquired during the initial practice session. These researchers concluded that texture discrimination learning involves a consolidation process which likely arises during the practice session, then subsequently underlies enhanced perceptual sensitivity hours after the session ends.

Current neuropsychological evidence from animal studies suggests that the hippocampal circuit—the initial site of memory encoding, known to be highly plastic—repeatedly reactivates circuits associated with new learning prior to memory storage in the neocortex (Carr, Jadhav, & Frank, 2011). Reactivation, or *awake replay*, occurs during short periods when exploration is suspended and is predictive of subsequent memory strength. Importantly, such mental replay occurs outside of behavioral repetition, thus providing a possible mechanism underlying improvement during offline periods in human learning experiments.

In one test of the awake replay phenomenon in humans, Dewar, Alber, Butler, Cowan, and Della Sala (2012) assessed recall of story units after participants either wakefully rested (i.e., sat quietly) or played a visual game on the computer during an interpolated gap. Memory for the verbal material was enhanced when the retention interval was uncluttered with additional external stimuli. Moreover, the observed memory improvement maintained for 7 days beyond the original exposure to verbal prose. Earlier, Dewar, Garcia, Cowan, and Della Sala (2009) showed that retention of verbal information by amnesic patients was improved as a function of delay length before an interfering task that was introduced following learning. Once again, immediate but not delayed mental activity disrupted memory formation for these individuals. Both the Dewar et al. findings and the Carr et al. (2011) animal learning evidence are consistent with Wixted's (2004) argument that everyday memory formation is hindered by subsequent mental exertion as opposed to mental quietude. In light of the gap improvement observed in the pilot experiment, this further suggests that memory strength for newly learned cognitive skills could be influenced by the nature of interpolated activity during practice.

Evidence of consolidation processes is not found across all memory systems or learning conditions, however. Robertson, Pascual-Leone, and Press (2004) practiced participants on the serial RT task, then tested them for both implicit and explicit sequence learning. Implicit learning did not occur during a 15-min retention interval but was exhibited to a significant degree over either 12 hr of wake or a 12-hr period that included sleep. (Interestingly, explicit sequence learning occurred only after the sleep period, not after the 12 hr without sleep.) Using a finger-tapping task, Hotermans, Peigneux, de Noordhout, Moonen, and Maquet (2006) noted an increment in posttraining skill after gaps of 5 min and 30 min, but not after 4 hr. In an imagery study, Debarnot, Clerget, and

Olivier (2011) replicated the boost in finger-tapping learning after a 30-min break both for subjects who engaged in physical practice and those who merely imagined themselves performing the movements. Unfortunately, none of these researchers specified what was done during the break; we know only that participants were not practicing the skill. In each of these cases, gap facilitation is attributed to time-dependent (as opposed to sleep-dependent) consolidation processes.

Release from PI

The second underlying mechanism hypothesized to affect skilled performance during training is PI, the disruptive influence of past processing on current processing (Kroll, Bee, & Gurski, 1973; Underwood, 1957). Under the PI scenario, interference accumulates over massed procedural practice but subsequently dissipates when practice stops, allowing for improved performance upon resumption of training. However, the typical paradigm for detecting PI effects involves declarative rather than procedural learning via the sequential presentation of lists of to-be-remembered information. During testing, memory for the earlier lists studied would be stronger than memory for later lists, evidencing that previously acquired memory traces proactively interfered with access to new information.

PI is a considerable source of forgetting (Nairne, Neath, & Serra, 1997), errors, and confusion (Wickens, Born, & Allen, 1963) in short-term retention. In a critique of empirical research on interference effects in list learning, Underwood (1957) asserted that, though retroactive interference is frequently identified as the culprit behind forgetting in experiments, PI is actually the predominant cause. Retroactive interference occurs when new material hinders retrieval of old material, but in laboratory studies of verbal learning participants are typically subjected to repeated cycles of memorization due to differing conditions and counterbalancing. The result is that they end up memorizing many lists, raising the possibility that previous lists do the interfering, not new lists. In an analysis of 14 studies of this type, Underwood found that the greater the number of previous lists learned, the more likely forgetting would be observed. In other words, "the greater the number of previous lists learned, the greater the *proactive* interference" (p. 53, italics in original). In the procedural learning portion of my pilot study, participants repeatedly and speedily solved block after block of highly overlapping problems which, especially initially, required explicit recollection, then application, of verbal rules. It seems plausible that the greater the number of previous items solved, the greater the PI operating on each successive item. The analog in verbal research is the number of previously learned lists, with magnitude of PI increasing consistently as the number of prior lists increases (Underwood, 1945).

Though the target of Underwood's (1957) salvo was not cognitive skill acquisition but list memorization research, his observations recommend release from PI as a potential explanation for observed gap facilitation effects if basic principles of accumulation and dissipation of interference hold across domains. As to accumulation of interference, a well-established principle of PI is that a positive relationship exists between amount of PI accrual and degree of similarity between consecutive activities (Underwood, 1945; Wickens, Born, & Allen, 1963), materials, and situations (Underwood, 1957). In a recent test of whether implicit memory is immune to the disruption of interference, Lustig and Hasher (2001) declared that not only was the answer to their question no, but that similarity between target and nontarget items is a critical boundary condition. This may be due to competition for retrieval cues between newly and previously encoded memory representations (Anderson & Bjork, 1994; Anderson & Neely, 1996) and suggests a content-specific character to PI. Participants in the pilot study solved numerous similar, and therefore confusable, practice items in a single experimental context, presumably resulting in mostly shared retrieval cues for the rules and thus inviting a build-up of PI. Additionally, magnitude of PI accrual is known to be inversely related to length of retention interval (Postman & Keppel, 1977). As the delay between learning episodes increases, the dominance of recent learning decreases. To-be-learned items in the pilot study were presented at a rapid pace, with intertrial intervals of 1 s, creating circumstances ripe for the accumulation of PI.

A construct akin to proactive interference is present in the behavioral domain. The learning theories of Hull (1943, 1951) and Kimble (1948, 1949) hypothesize that even as an effortful response—primarily of a motor nature, for these researchers—to a stimulus is occurring, a corresponding tendency to avoid repeating the response accrues. In his two-factor theory of inhibition, Kimble explains that this avoidance is a drive and is termed *reactive inhibition*. Reactive inhibition is positively correlated with amount of effort expended and resembles fatigue in the sense that rest is necessary to dissipate it. However, *rest* in this context is an active goal response which is automatically initiated when a critical amount of reactive inhibition has accumulated. During resting periods, built-up reactive inhibition dissipates as a simple decay function of time, only to rebuild as the behavior which precipitated it, or *work*, resumes. Thus, a work-rest cycle ensues which eventually reaches a state of equilibrium. All the while, habit strength for the ongoing response increases with repetition, resulting in improvement in the dependent measures. Thus, both reactive inhibition and PI predict decrements in performance over practice and a performance benefit from a break due to the dissipation of task- or content-specific interference.

Ammons (1947) systematically investigated the work-rest cycle, but he referred to reactive inhibition as *temporary work decrement*. To test the effects of experimenter-imposed resting periods on procedural practice of a motor skill, this researcher utilized the pursuit rotor task and a large sample of female undergraduate participants ($N = 510$) to explore 35 interrelations between amount of prerest practice (5 levels, from 30 s to 17 min) and duration of rest break (7 levels, from 30 s to 360 min). He calculated improvement after rest, or *reminiscence* (a phenomenon originally identified by Ballard, 1913; see also Eysenck & Frith, 1977) due to dissipation of temporary work decrement, as the gain on the first postbreak trial over the expected level on that same trial had no rest been interpolated (from Buxton, 1943). All groups realized some amount of this version of gap facilitation, with maximal gains experienced by subjects who practiced for 8 min before resting. Task-specific fatigue dissipated for about 20 min after rest, with 90% of the recovery occurring within 5 min of discontinuing practice. Ammons attributed performance gains to a dissipation of the temporary work decrement.

With regard to the rate at which interference (or inhibition or decrement) dissipates, Underwood (1945) noted that PI effects were exceedingly transitory in his list-learning task, dispersing after only one trial (i.e., list). Adams and Dijkstra (1966) scheduled 3-min intertrial intervals in a simple linear motor response task to allow for appreciable trial-to-trial trace decay, while Peterson and Peterson (1959) found virtually no recall of conditioned elements (consonant syllables) after 18 s. Taken together, these studies suggest that in the pilot experiment, disengaging from procedural learning midway through practice and engaging in a different task for 12 min was likely ample time for interference effects to ebb.

Mental Rest

Researchers as far back as Ebbinghaus (1885/1964) have studied the adverse toll prolonged mental work takes on cognitive functions such as memory, judgment, and reasoning. Often the culprit task characteristic is sheer length of time on task, with periods of sustained effort in a single cognitive task leading to declines, or vigilance decrements, in performance that are an increasing function of task duration (Davies & Parasuraman, 1982). In an extreme example of the time-on-task effect, Arai (1912) examined cognitive fatigue by subjecting herself to a 4-day ordeal during which she mentally solved 4-digit multiplication problems (one multiplier and one multiplicand) from 11:00 a.m. to 11:00 p.m. without food or break. Quite understandably, she noted progressive lessening of her abilities, with time taken to solve one problem more than doubling by the end of a 12-hr session. Interestingly, her subjective opinion was that "the apparent loss in efficiency (was) due to physical weariness and consequent boredom rather than to loss in mental capacity to perform the task" (Huxtable, White, & McCartor, 1946, p. 2).

More relevant here, however, is another task characteristic known to accelerate the build-up of mental fatigue: high level of demand on intellectual functioning. According to Ackerman (2011), "cognitive fatigue effects are typically associated more with tasks that require high levels of effort than with tasks that have low levels of effort" (p. 14). For example, cognitive task performance deterioration has been observed after only 10 min of continuous perceptual concentration (Dinges & Powell, 1985), and decrements in event-related potential (ERP) data have been noted after sustained work durations of no more than 20 min (Kato, Endo, & Kizuka, 2009; Van Dongen, Maislin, Mullington, & Dinges, 2003). Conversely, virtually no performance decrement was perceptible after 6 hr of reading text (Carmichael & Dearborn, 1947) or adding single-digit numbers (Kaneko & Sakamotor, 2001). In these cases, the determining factor in the formation of fatigue appears to be level of requisite mental effort, not time on task. Cameron (1973) noted that, especially in the physical realm, a relatively short period of time spent on a highly demanding task should result in an accumulation of fatigue similar to that produced by a minimally demanding task engaged in for a longer period of time.

Mental fatigue effects precipitated by continuous demands on attentional resources can be ameliorated by making the demands intermittent instead (Ackerman, 2011). Indeed, a brief rest period is sufficient to allow for the dissipation of the effects of performance declines after periods of practice (Cameron, 1973). A motor study by Adams (1955) provides an apt example of a level-of-demand manipulation. He varied the amount of cognitive effort required during a break activity to investigate elemental responses in pursuit rotor learning. Noting that a subject's score on any complex psychomotor task is essentially a composite score representing skill attainment across more than a few component responses, he manipulated an interpolated task to impact the visual response component. Subjects were assigned to one of five break activities which varied as to the amount of continuous visual and physical effort required, and the opportunity to rest. Pertinent here is the finding that all the groups enjoyed substantial postbreak skill increases regardless of break type or length of rest (either 10 or 15 min).

Additionally, the more restful the break activity, the more postbreak time on target (i.e., skill improvement) participants achieved. Of course, performance improvements in a psychomotor task following a break could be from physical in addition to mental rest, and presumably this would not be a contributing factor in gap facilitation for a cognitive skill.

As noted earlier, ostensibly different processes underlying gap facilitation might operate together and be difficult to distinguish. Nevertheless, to the extent possible, the current research attempts to test the independent contributions of consolidation, release from PI, and mental rest.

CHAPTER 3

PILOT EXPERIMENT

The purpose of the pilot study was to investigate the effect of interpolating a simple associative task midway through multiple blocks of practice of a moderately complex cognitive skill. The results precipitated the present experiment, which utilized a variant of the same learning task and different interpolated tasks designed to test alternative explanations for observed gap facilitation.

Method

Participants and Design

Participants were drawn from the Educational Psychology Department subject pool during the 2011-2012 school year at the University of Utah. Of the original 73 subjects, 22 (30%) were eliminated due to either high error rates during learning or poor model fits (described later). The final sample (N = 51) included 40 females and 11 males ranging in age from 18 to 52 years.

The between-groups design, shown in Table 3.1, had two conditions, NoGap and Gap, which differed only as to the temporal placement of the interpolated task, *Digit Symbol*, in relation to blocks of skill practice. The experiment was programmed using E-Prime (Schneider, Eschman, & Zuccolotto, 2002), and most subjects finished in less than 1 hr while seated at a computer.

<u>Learning Task</u>

Participants learned to perform a sequential processing skill in which they made judgments involving electrical circuitry operations called logic gates. Logic gates have been used extensively by others investigating cognitive skill acquisition (e.g., Carlson, Khoo, Yaure, & Schneider, 1990; Carlson, Sullivan, & Schneider, 1989; Gitomer, 1988; Kyllonen & Woltz, 1990) and have high utility in the university laboratory setting because college students outside of engineering fields are, as a rule, ignorant of them.

To become skilled at solving logic gates, participants began by learning declarative rules for two gates, AND (A) and OR (O), through verbal instructions, single-gate practice, and individual-item corrective feedback. The wording of the rules was as follows:

AND rule: If BOTH inputs are 1, then the output is 1. Otherwise, the output is 0.

OR rule: If EITHER input is 1, then the output is 1. Otherwise, the output is 0.

The gate symbols themselves were brackets for A, <   >, and parens for O, (   ) (see Carlson & Yaure, 1990, for a similar gate symbol variation). Inside the brackets and parens were binary inputs, always some combination of 0 and 1. Depending upon the type of gate (A or O) and the combination of inputs (0-0, 0-1, 1-0, or 1-1), an output of either 0 or 1 was determined for each gate. In all, participants practiced eight unique visual presentations of single gates. Pair practice (sequences of A-O and O-A) preceded three-gate ("trio") practice (sequences of A-O-A and O-A-O). The goal for participants was to become skilled at solving trio items (one of which is depicted in Figure 3.1 in a three-screen sequence).

To successfully perform each trio trial, the learner was required to execute the following multistep process:

1. Upon viewing Screen A, determine, then type, the output to the first gate based on gate type and displayed inputs.
2. At the appearance of Screen B (note that the contents of Screen A are still visible in B), mentally replace the asterisk in the second gate with the output from the first gate.
3. Determine and type the output to the second gate.
4. When Screen C appears, mentally replace the asterisk in the third gate with the output from the second gate.
5. Determine and type the final output to the trio.

None of the typed outputs appeared on the screen, nor was immediate trio feedback given during the procedural practice blocks. RT and errors for each individual gate were collected, and summary feedback was displayed at the end of each block. The bulk of the experiment consisted of procedural practice of a total of 256 trio items organized into two sets of eight blocks of 16 trio items. Each of the 32 unique trio items possible (2 trio sequences x 16 different input combinations) was seen every 2 blocks in randomized order per subject.

Gap Task

The Digit Symbol task served as the interpolated activity for all participants. The version used was a computerized, partially verbal variation of the Digit Symbol Substitution Test contained in the Wechsler Adult Intelligence Scale (WAIS-III, 1997). In this speeded, associative, "look-up" task, each trial displayed digits *1* through *6* paired with one of six nonwords (consonant-vowel-consonant, or CVC, format) immediately beneath, as shown in Figure 3.2.

In Digit Symbol, the same digit and nonword were always paired (e.g., 6 and *tib*), but the horizontal serial order of the pairs changed randomly on every trial. The ever-present display across the top of the screen comprised an answer key, of sorts, to which subjects could always "look up," thus providing an "errorless" learning paradigm. Near the center bottom of the screen on each trial, a horizontally oriented digit and CVC appeared, sometimes as paired at the top (a "like" pair, as in Figure 3.2) and at other times paired differently (a "different" pair; e.g., 6 and *mef*). In a two-choice response format, participants pressed "D" or "L" for different or like, respectively, under instructions to respond "as quickly and accurately as possible." It was considered mildly demanding, at best, because the answers were always shown. To discourage deliberate memorization of the stimulus pairs (and thus maintain the implicit nature of the task), the amount of time allowed for responding in each of the eight blocks gradually decreased from a maximum of 6 s per display in the first practice block to 3 s in the final two blocks.

As shown in Table 3.1, participants in the Gap group engaged in the Digit Symbol task after they had completed eight blocks of trio practice, with one re-orienting screen appearing at the beginning of the second set (Blocks 9-16) of practice blocks. Participants in the NoGap group engaged in Digit Symbol at the outset, then completed two eight-block sets of trio items. The sets were separated by a single screen informing participants that eight more blocks of practice would follow.

Results

Figure 3.3 displays the mean RT data by trial block for both groups. Above each trial block are three vertically stacked data points. Each point represents the mean RT for Gate 1, 2, or 3 of the 16 trio items occurring during a given block. Average response latency declined for all three gates with continual practice, but an interesting pattern of RT is associated with the ordering of gate latencies within a block. During Set 1 for both groups, participants typically took the longest to solve Gate 2. This is possibly because determining the answer to this second gate required participants to carry forward an intermediate solution, 1 or 0, from Gate 1, a process which was not necessary for solving Gate 1. With practice, the predictability of this Gate 1 advantage lessens for the Gap group, and largely disappears for the NoGap group. Gate 3 RT, however, are often the fastest across both groups. This observation is potentially due to the anticipation of rule transitions inherent in implicit sequence learning developed across practice blocks (see Carlson & Shin, 1996; Woltz, Gardner, & Gyll, 2000).

Accuracy data were not included in the analyses because, after eliminating 11 subjects (5 from the Gap group and 6 from the NoGap group) due to error rates greater than 30%, there was no difference in mean accuracy between the groups (NoGap = .952, Gap = .949, $F < 1$).

Modified Power Function

The overall shape of both learning curves was nonlinear, as expected, but closer inspection revealed an immediate drop in RT (i.e., improvement) in the Gap group between Blocks 8 and 9, when that group stopped practicing and engaged in Digit Symbol. To quantify the apparent facilitative (in this case) effects of the break, the power function was altered from its original form to include an additional parameter *m*:

$$T = a*(N+m*Set)^{-b}, \qquad [2]$$

where T, as before, is performance time at a given practice event, *a* is initial performance time, N is the number of practice events, or blocks, and *b* is the learning rate ($b < 0$). Parameter *m* (theoretically, $-\infty \leq m \leq \infty$) accounts for learning, or memory strength, accrued outside of current practice events (N). "Set," coded as either 0 or 1, separates Practice Blocks 1-8 (Set 0) from Practice Blocks 9-16 (Set 1) and ensures that *m* is allowed to be estimated only with respect to trial blocks following the interpolated task manipulation (i.e., when Set = 1). Thus, *m* is conditional upon the break. Such an alteration is not unprecedented; the power function has been changed as needed to clarify performance time improvements with practice (Newell & Rosenbloom, 1981). (Parameter *E* is absent in the modified function because prior experience with the task was not allowed among the participants. Additionally, an asymptote parameter was not included due to the modest amount of practice provided.)

<u>Analysis of Individual Data</u>

Some researchers have noted that, when attempting to determine a functional relationship for groups of subjects, the mean curve is often insufficient for describing individuals (Estes, 1956; Heathcote, Brown, & Mewhort, 2000; Sidman, 1952). Consequently, each participant's mean RT for each of the three gate responses across the 16 blocks (48 data points) was fitted with the modified power function described above. The model fit most participants' data well. However, as noted earlier, data from 11 subjects (4 from the Gap group and 7 from the NoGap group) were poorly fit by the power function. Given the goal of comparing model parameters between groups, participants for whom the model did not fit (i.e., those with fits of $R^2 < .3$) were eliminated from subsequent analyses. Of the remaining 51 subjects, the mean R^2 was .62 (range .35 to .88).

Estimated values of *m* for those interrupted by the interpolated task were within a plausible range (*M* = 12.72, *SD* = 14.56). In other words, an *m* value of 12.72 indicates that Gap participants gained, on average, the equivalent of almost 13 "blocks worth of practice" from the break. (A positive *m* value reflects improvement, while a negative *m* value reflects a decrement.) This average 12.72-block increment roughly corresponds to the 165 ms mean change between Blocks 8 and 9 for the Gap group shown in Figure 3.3. By contrast, the NoGap group's mean *m* parameter was smaller (*M* = 3.27, *SD* = 6.24), roughly corresponding to their 36 ms mean change from Block 8 to 9. The mean *m* values differed significantly between the two groups, $F(1, 49) = 8.95$, $p = .004$, $\eta_p^2 = .15$.

<u>Postbreak Performance</u>

Note in Figure 3.3 that the fit for the means of the Gap group does not fully capture their data because of their slight increase in RT during Practice Blocks 9-16. Another relevant aspect of Figure 3.3 is that participants in the Gap group, despite the boost in their scores at Block 9, realized no net skill improvement thereafter (mean linear slope of final eight blocks = -.003). However, the NoGap group steadily improved (linear slope of final eight blocks = -.161), resulting in an interaction of the linear effect of block and condition following the break, $F(1, 49) = 15.43$, $p < .000$, $\eta_p^2 = .24$. There was no main effect of group for the final four practice blocks, $F(1, 49) = 1.15$, $p = .29$.

Discussion

For participants in the Gap group, switching to a different activity in the middle of procedural practice of a cognitive skill resulted in a disproportionate amount of skill improvement upon resumption of practice relative to the NoGap group, as quantified by parameter *m* (12.72 and 3.27 blocks of postbreak advancement, respectively). The reason for the improvement, or gap facilitation, is not understood, but three potential explanations are posited here: (a) memory consolidation of the gates rules occurred during the break in practice, thus strengthening memory traces for the nascent cognitive skill; (b) participants experienced a release from PI which had built up during the first eight blocks of similar—and therefore confusable—trio items, allowing for faster postbreak responding; and (c) participating in a nondemanding activity during a short gap in practice blocks enabled participants to mentally rest from effortful, rule-based learning and perform with renewed vigor after the break.

A fourth plausible explanation for gap facilitation was considered, then rejected, in the formulation of the dissertation study. Under this supposition, the rapid cadence of the Digit Symbol interpolated task instantiated in Gap group participants a speeded response set which carried over to the second set of procedural practice blocks. For the NoGap subjects, Digit Symbol came first; any momentum that may have built up from speeded responding likely dissipated during the slow-paced instructional portion of the learning task.

A statistical test was performed (on Gap group data only) to explore this alternative explanation for gap facilitation. First, if the speeded response set explanation were operating, mean RT from the last few blocks of the interpolated task, Digit Symbol

Blocks 6, 7, and 8, should add to the predicted mean RT performance on immediate postbreak Practice Blocks 9, 10, and 11 beyond what is predicted by mean RT from prebreak Practice Blocks 6, 7, and 8. This, however, was not the case. Though Digit Symbol Blocks 6, 7, and 8 correlated significantly with Practice Blocks 9, 10, and 11, $r(26) = .49$, $p = .011$, the correlation between prebreak Practice Blocks 6, 7, and 8 and postbreak Practice Blocks 9, 10, and 11 was much higher, $r(26) = .90$, $p < .001$. Checked another way, mean RT in Practice Blocks 6, 7, and 8 alone significantly predicted mean RT in Practice Blocks 9, 10, and 11, $b = .73$, $t(26) = 8.33$, $p < .001$; adding the influence of mean RT in Digit Symbol 6, 7, and 8 contributed virtually nothing to the model, $b = -.02$, $t(26) = .08$, $p = .84$.[1] In addition, smaller pilot experiments not reported here evaluated the gap effect from different interpolated tasks that did not emphasize RT. Participants with these nonspeeded break tasks showed similar gap facilitation effects. Based on these findings, the speeded response set explanation for gap facilitation was not considered further.

---

[1] The simple correlation between mean RT for eight blocks of Digit Symbol and gap change *m* was $r(51) = .18$, $p = .209$.

Table 3.1

Design of Pilot Experiment

Experimental Groups	Tasks		
	Part 1	Part 2	Part 3
NoGap	Digit Symbol task	Practice Blocks 1-8	Practice Blocks 9-16
Gap	Practice Blocks 1-8	Digit Symbol task	Practice Blocks 9-16

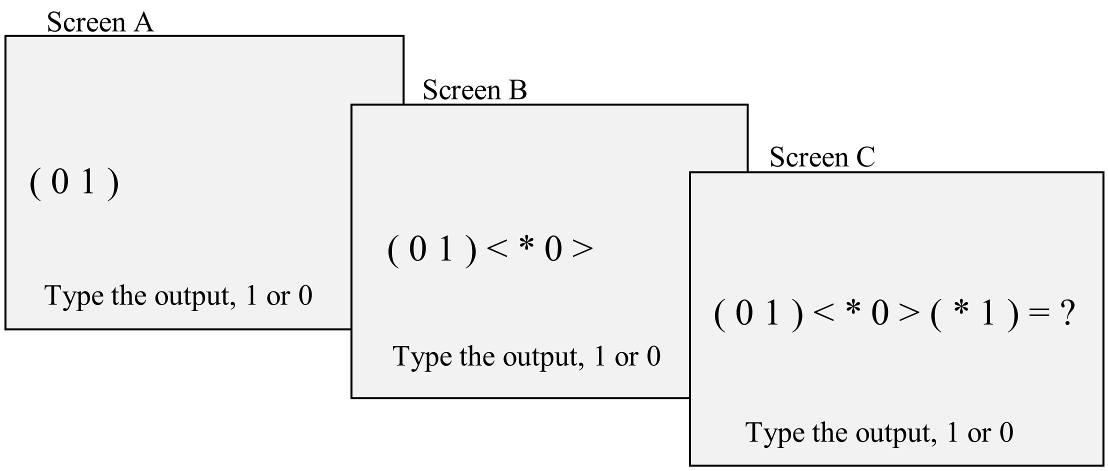

Figure 3.1. A sample O-A-O trio ítem.
Notes. The item is depicted on three separate, sequential slides, as shown to participants. Screen A contains the first (OR) gate, Screen B displays the addition of the second gate (AND, in this example), and Screen C adds the second OR gate, representing one complete practice ítem.

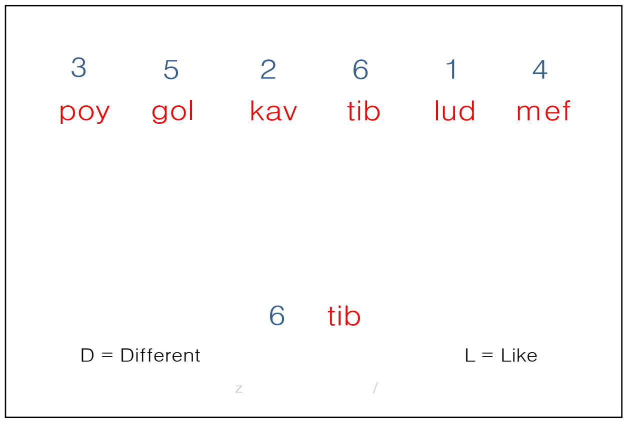

Figure 3.2. A single trial of Digit Symbol.

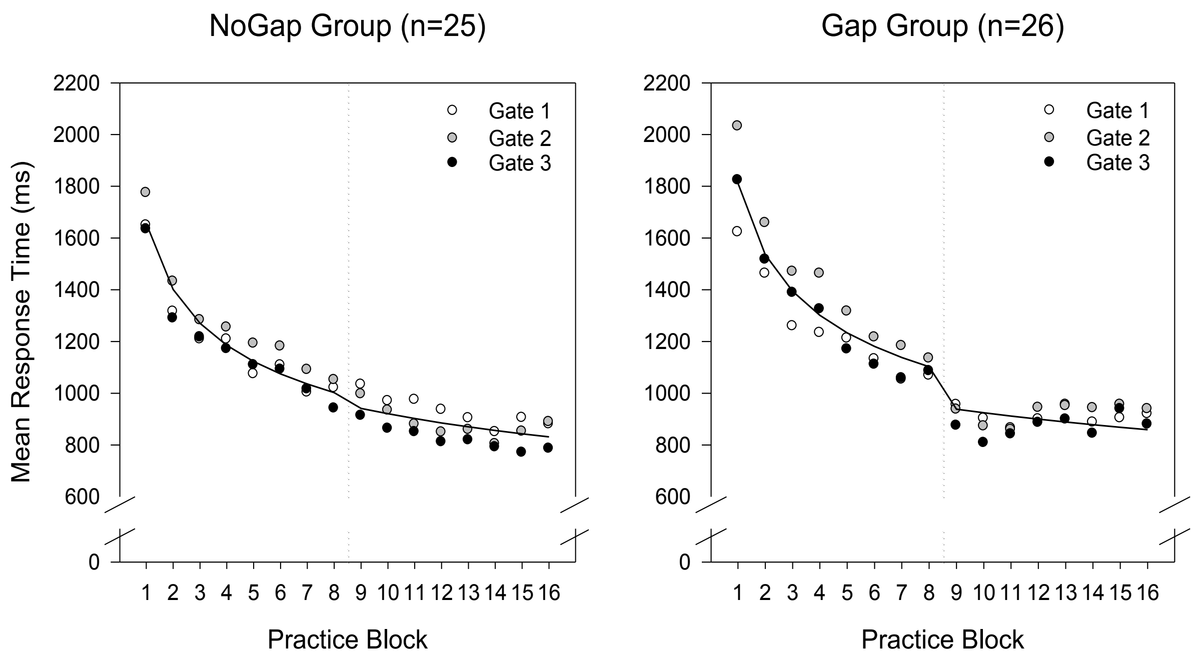

Figure 3.3. Mean RT for logic gate blocks by gate position and gap group.
Notes. Dashed lines indicate the interval during which the NoGap group continued practicing but the Gap group switched to Digit Symbol. Lines of best fit are in accordance with the modified power function fitted to mean group data.

CHAPTER 4

OVERVIEW OF THE EXPERIMENT

Inasmuch as none of the three plausible explanations for gap facilitation described earlier were uniquely supported by data from the pilot study, this research project was conducted to investigate the effects of varying the cognitive demands of the activity interjected into the logic gates skill practice. Two gap activities were selected, one designed to minimize cognitive demand with an activity conducive to rest and the other to increase cognitive demand by requiring engagement in an effortful WM activity over the same period.

To the extent the desired effects were achieved, this experimental manipulation differentiated between the three explanations because each makes a unique prediction regarding the impact of restful versus effortful activity during the break. Specifically, if mental rest is the cause of gap facilitation, the group that was instructed to rest during their break would exhibit a temporary burst of faster RT afterward, while the group that performed an effortful task would exhibit slower RT relative to continuous power law learning. If memory consolidation is responsible for gap facilitation, the absence of cognitive demand associated with the restful group would invite recently formed memories to undergo early stabilization processes; thereafter, this group would exhibit an enduring postbreak benefit to performance. For the group whose WM demands precluded consolidation processes from ensuing during the break, however, postbreak RT would not differ from what would be expected under continuous power law learning. Lastly, under the release from PI explanation, postbreak performance would be affected by the fact that a gap activity took place but would be unaffected by the nature of the gap activity. The inhibitory potential of PI is postulated to spontaneously dissipate with the passage of time as soon as the activity which produced it ceases, but to build again as the same activity resumes (Hull, 1951). Thus, performance gains would be short-lived.

From the preceding explication of predicted postbreak performance patterns, it is apparent that not only immediate but sustained gap effects needed to be measured. Persistence of learning was thought to be better quantified in this experiment than in the prior study due to the estimation of one additional parameter, *b2*, in the already-modified power function model, when the other parameters were fixed:

$$\mathrm{T} = a*(\mathrm{N}+(m*\mathrm{Set}))^{(b+(b2*\mathrm{Set}))}, \qquad [3]$$

where T represents performance time at a given practice event, a is initial performance time, N is the number of practice events (in this case, blocks), m is gap change between Blocks 8 and 9, and b is the learning rate ($b < 0$). After being estimated when the other parameters are fixed, *b2* is added to learning rate b and reflects the possible change in the trajectory of learning during postbreak Practice Blocks 9-16. "Set," coded as either 0 or 1, separates Practice Blocks 1-8 (Set 0) from Practice Blocks 9-16 (Set 1) and enables the incremental estimation of targeted parameters with respect to trial blocks before or following the interpolated task manipulation. All predictions and associated statistical procedures and tests are explained in detail at the conclusion of the Method chapter (Chapter 5).

The to-be-learned skill task entailed the sequential, three-step application of two rules for electrical circuitry operations (i.e., logic gates), a variant of the task utilized in the pilot study. (As before, nonnaïve subjects were excluded.) The experimental manipulation of interest occurred during a break injected midway through skill practice. The break was filled by either a cognitively demanding (CD) *N*-Back WM task or a purportedly relaxing, noncognitively demanding (NCD) listening activity. The rationale for each of these new gap tasks is given next.

CD Gap Task: *N*-Back

Participants in the CD group performed the *N*-Back task as a break activity due in part to its extensive use as a WM task. *N*-Back is considered demanding because participants must continuously update an ever-changing rehearsal set while providing regular responses to displayed items (Kane, Conway, Miura, & Colflesh, 2007). Originally conceptualized as a paced tasked and designed to investigate very short-term retention (Kirchner, 1958) , this continuous-recognition paradigm has proven useful in experimental research (Jaeggi, Buschkuehl, Perrig, & Meier, 2010) and, more recently, in neuroimaging studies involving techniques such as functional magnetic resonance imaging (fMRI; Owen, McMillan, Laird, & Bullmore, 2005).

In a standard *N*-Back configuration, familiar stimuli (e.g., positive integers) are presented at a fixed rate and location on a computer screen, and participants are required to indicate with a keypress whether the currently displayed stimulus matches the stimulus shown *N* positions back or not. Cognitive demands increase with increases in required attention and task arousal, in general (Kahneman, 1973), and are positively correlated in this task with *N* (typically 0, 1, 2, or 3). Therefore, I utilized *2*- and *3*-Back variations to induce a high level of mental effort in participants. To avoid perceptual overlap with the logic gates symbols, alphabet letters were displayed rather than numbers.

NCD Gap Task: Binaural Beats

Although relaxing music is frequently the stimulus of choice in empirical research comparing cognitive processing under varying emotional states (e.g., Chafin, Roy, Gerin, & Christenfeld, 2004; Scheufele, 2000), any prior exposure to a musical selection is known to activate specific contents of semantic and episodic memory (Eschrich, Munte, & Altenmuller, 2008; Jancke, 2010). To circumvent this extraneous variability, I used nonmelodic auditory modulations called binaural beats in an attempt to induce a relaxed state in participants assigned to the NCD condition.

Binaural beats are produced when two tones of similar—but not identical—frequency are presented separately and simultaneously into each auditory channel through stereophonic headphones. Each ear hears only one frequency, but the brain produces a composite signal, or beat, with an amplitude frequency that is the difference between the two that were heard. Hypothetically, the binaural beat “entrains the brain toward a desired frequency” (Lavallee, Koren, & Persinger, 2011, p. 352) by stimulating synchrony with electroencephalographic (EEG) activity. Thus, a binaural beat frequency can be selected so as to stimulate an associated EEG state. For example, suppose a pure tone of 410 Hz were introduced into one ear and a pure tone of 400 Hz into the other ear at the same moment. Inside the listener’s head, an auditory beat with amplitude 410-400, or 10, Hz would be generated and, through entrainment, produced throughout the rest of the brain (Padmanabhan, Hildreth, & Laws, 2005).

The applicable literature on binaural beats is small and somewhat varied. Researchers depending solely on subjective measures of participants’ emotional states after listening to recordings have found decreased presurgery anxiety (Padmanabhan et al., 2005) but minimal impact on insomnia (Alexandru, Robert, Viorel, & Vasile, 2009). Others have either succeeded at finding (e.g., Kasprzak, 2011; Lavallee et al., 2011; Schwarz & Taylor, 2005) or failed to find (e.g., Brady & Stevens, 2000; Wahbeh, Calabrese, Zwickey, & Zajdel, 2007) evidence of entrainment in EEG readings. In one study that may be of particular interest here, Lane, Kasian, Owens, and Marsh (1998) combined a self-report measure of mood with an accuracy score. Over 3 days, participants completed the same computerized vigilance task (similar to *1*-Back) three times while listening to what they thought were the same nondescript sounds. On two of the days, however, the sounds were masking binaural beats in either the delta/theta range (associated with drowsiness) or the beta range (associated with alertness). Scores on subjective measures of confusion/bewilderment and fatigue/inertia were significantly higher (i.e., worse) when participants had listened to the delta/theta beats. Behaviorally, subjects were significantly better at both detecting targets and avoiding false alarms when they had listened to beta-wave beats.

As a result of the foregoing investigation into binaural beat technology, NCD participants were exposed to a recording of alpha-wave beats overlaid with ethereal tones. Alpha waves oscillate at a range of about 8-13 cycles/sec and are present during deep relaxation.

CHAPTER 5

METHOD

Participants and Apparatus

Participants were drawn from the Department of Educational Psychology subject pool and from the University of Utah student population at large. They received course credit or $20 ($5 after Session 1 and $15 after Session 2), respectively, for participating in the experiment. Of the original 172 subjects, 32 (18.6%) were eliminated due to either high error rates during learning or poor model fits (described later). The final sample (N = 140) included 98 females and 42 males ranging in age from 18 to 69 years (M = 23.62).

Participants performed the experimental task on microcomputers with SVGA monitors and standard keyboards. Programming of the experimental task was completed with E-Prime software (Schneider et al., 2002). The software achieves millisecond timing of response latency. Participants were required to wear the stereophonic headphones, which were provided, throughout the experiment.

Design and Procedure

The between-groups design is depicted in Table 5.1. Subjects were randomly assigned to one of four experimental conditions: CD-Gap and NCD-Gap (the *Gap* groups), or CD-NoGap and NCD-NoGap (the *NoGap* groups). The *N*-Back and binaural beats interpolated activities are referred to as *break* or *gap* tasks for all groups, even though they were performed at the beginning of the experiment (i.e., prior to any learning) for the NoGap groups. The NoGap groups were included in the experimental design under the assumption that their skill improvement across 16 uninterrupted blocks of practice would provide a measure of typical, power-law skill improvement against which the Gap groups could be compared.

Participants in all experimental conditions learned to solve logic gates problems via the same instructional and training formats used in the pilot. However, rather than limit the skill practice to two trio sequences (A-O-A and O-A-O), this experiment utilized four different sequences out of the eight possible three-gate combinations. Trios A-O-O, A-A-O, O-A-A, and O-O-A were selected for skill acquisition because they balance the occurrence of each gate at each serial position and eliminate sequences that have three identical gates in a row.

<u>Practice Blocks</u>

The remainder of the experiment consisted of procedural practice of a total of 256 trio items organized into two sets of 8 blocks of 16 different trios each. Each of the 64 unique trio items possible (4 trio sequences x 16 different input combinations) was seen every four blocks in randomized order per subject, and thus was solved four times. As before, none of the outputs appeared on the screen as they were typed, and summary error and latency trio feedback was displayed at the end of each block to facilitate motivation in subjects across repeated blocks of practice.

After the first set of eight practice blocks, Blocks 1-8 (Set 1), Gap group participants engaged in their respective gap tasks, CD (*N*- Back) and NCD (binaural beats), before completing the second set of eight Practice blocks, Blocks 9-16 (Set 2).

The two NoGap groups completed their gap tasks at the beginning of the experiment and consequently moved through Sets 1 and 2 with only one re-orienting slide between Blocks 8 and 9 that simply informed them of eight more blocks of the same task. Both gap tasks were of precisely the same duration to ensure a consistent length of time across all subjects regardless of condition.

N-Back Gap Task

Trials were presented in blocks of 30 and consisted of one centered letter per screen, which appeared for 500 ms, then disappeared. Participants were instructed to respond to each trial by pressing a key marked *yes* or a key marked *no,* depending on whether the current letter was identical to that seen *N* frames earlier. (*N* was restricted to either *2* or *3* in this experiment.) The next trial began 2000 ms after the disappearance of a stimulus regardless of whether the participant responded or not (i.e., a new trial began every 2500 ms). Consequently, an entire block lasted 1:15 min.

A sample subset of six trials in a *2*-Back series is depicted in Figure 5.1. In this example, participants should respond *no* to the first three trials and *yes* to the fourth trial because the fourth stimulus shown, *D*, is the same letter as was shown *2* slides back. The last two trials in this example would again require *no* responses. In a given block of 30 trials, there were between five and 10 trials requiring *yes* responses. Response accuracy for all trials is the measure of interest. Failure to respond before the next stimulus is presented was counted as an error. As feedback, participants were provided with mean accuracy and latency scores at the end of every block.

The *2*-Back level of *N*-Back occurred first for all CD participants and consisted of three blocks. Before beginning, participants viewed a series of 12 instructional slides that unfolded on a timed basis and were accompanied by an audio recording explaining the currently presented image. Three blocks of *3*-Back items followed, which mirrored the *2*-Back blocks in every way except during the instructional portion, when *yes* responses were described as being required if a stimulus was the same as the one appearing "*3* screens back." The ratio of *yes* responses to *no* responses at both *N*-Back levels was 1:2 in Block 1, 1:4 in Block 2, and 1:5 in Block 3 (adapted from Kane et al., 2007). At the conclusion of *3*-Back, participants viewed one re-orienting screen before resuming trio practice. The entire *N*-Back task, including instructions and three blocks each of *2*-Back and *3*-Back, lasted exactly 14:40 min.

Binaural Beats Gap Task

To facilitate relaxation in the NCD condition, participants were first informed that they were about to engage in a different activity in which "the expectation is that you rest." The goal of the manipulation was relaxation, so participants heard the instruction to "free yourself from the cares of the day." No other direction was given as to what the content of their thoughts should or should not be during the break. They were asked to push their keyboard out of the way, don a set of dark goggles located nearby, and put their head down as a recording of binaural alpha-wave beats began playing quietly over their headphones. At 5-min intervals, a quiet, overlaid voice informed them of the time remaining for resting. At the conclusion of the beats period, participants were told to remove their goggles, replace their keyboard, and resume trio practice. As with the NoGap groups, there was one re-orienting screen informing them of eight more blocks of practice. The entire nondemanding break, including instructions and listening portion, lasted 14:40 min.

Fatigue Ratings

As a manipulation check of whether the interpolated *N*-Back and listening tasks were perceived as cognitively demanding and noncognitively demanding, respectively, self-report ratings of fatigue were administered at the conclusion of Session 1. Participants were asked to retrospectively rate, on a scale from 1 (*not at all fatigued*) to 9 (e*xtremely fatigued*), how mentally fatigued they felt at four points in time: *Time 1*—upon arriving at the lab, *Time 2*—at the beginning of the nonlogic gates gap task (N-Back—the CD task, or listening to binaural beats—the NCD task), *Time 3*—at the end of the gap task, and *Time 4*—at the end of the experiment.

Retention Phase

Six to 8 days after participating in Session 1, subjects earned additional course credit, or the bulk of their pay, by returning to the same location to complete the retention portion. After one brief welcome screen but no review information whatsoever, participants solved four more blocks of 16 randomly presented trio items as a test of how well they had retained their recently acquired skill. All 64 unique trio sequences and stimulus combinations—seen four times each in the Session 1 practice blocks—were seen once in the retention phase. RT and accuracy feedback were given at the end of the fourth retention block only, concluding the second and final session of the experiment.

Hypothesized Result Patterns

Based on the nature and temporal placement of the interpolated tasks, at least four patterns of RT change could have been manifested that correspond to the previously discussed explanations for gap effects. These are depicted in the quadrants of Figure 5.2. Note that all plots are identical until Practice Block 8 because, although participants in the NoGap groups had already experienced a gap activity, the learning task instructions and initial practice blocks did not differ between groups.

Quadrant 1: Strength Decay

There should be no difference between the two Gap groups under this explanation. According to the power law of practice, memory strength for to-be-learned material decreases during periods of nonpractice. Both the CD- and NCD-Gap groups disengage from the same learning task for the same amount of time after the same eight blocks of practice and thus should undergo the same amount of forgetting during their break, regardless of the character of the break activity. Forgetting would result in higher (i.e., worse) initial postbreak RT, but negative effects should be short-lived as memory strength accrues anew with practice. At the conclusion of Practice Block 16, RT for both Gap groups would be close to, but nonetheless slower than, the NoGap groups. The NoGap group should suffer no loss in RT between Blocks 8 and 9 because they experience no interruption of their practice. Although this prediction is inconsistent with the facilitation found in the pilot study, it represents the expectation of a pure power law prediction of memory strength accrual and decline with a gap in practice.

Quadrant 2: Mental Rest

If mental rest during the break is responsible for gap facilitation, the NCD-Gap group should enjoy a drop (i.e., a speeding) in RT following their relaxing interpolated activity. The CD-Gap group, which performs a WM task presumed to be more taxing than continued skill practice, should experience a corresponding negative effect on postbreak RT. However, if having a chance to mentally rest causes gap facilitation, the implication is that the learning task was tiring to some degree. As such, any positive effects from resting would be temporary as participants' fatigue increases again during Practice Blocks 9-16, resulting in a postbreak learning rate that slows relative to that of the NoGap groups.

Quadrant 3: Memory Consolidation

If memory consolidation is responsible for gap facilitation, it should manifest as significantly faster RT in Practice Block 9 only for participants in the NCD-Gap group. This group's period of mental quietude ostensibly would allow for various elements of recently encoded information to strengthen to a greater extent than was possible for the CD-Gap participants, who were required to manage a heavy WM load during the break. CD-Gap participants should experience no offline stabilization of logic gates learning and may evidence a small initial decrement in performance (i.e., slower RT) due to nonpractice before resuming prebreak learning rates. Importantly, the memory consolidation explanation for gap facilitation predicts no change in the rate of learning (b) of NCD participants after the break. Though the trajectory of NCD-Gap participants' postrest learning curve appears in Figure 5.2 to have flattened (i.e., weakened), this is an accurate depiction of an unchanged learning rate. It merely reflects the increasingly asymptotic character of their learning curves after they realize m blocks of improvement during the gap activity. A consolidation benefit would be a persistent increment to strength that steadily grows with continued practice.

Quadrant 4: Release from PI

If release from PI is the reason for gap facilitation upon resumption of procedural learning, both the NCD- and CD-Gap groups should be identically affected. Each discontinues practice to engage in an activity dissimilar to the learning task, theoretically allowing interference from repetitions of the practiced items to dissipate. The immediate positive effects should be short-lived, however, as PI once again builds up during the second set of practice blocks. By the end, RT should be similar to those of the NoGap groups, as was the case for the mental rest prediction for the NCD-Gap group in Quadrant 2.

Table 5.1

Design of Experiment

Condition	Task 1	Task 2	Task 3	Retention
CD-Gap	Gates instruction and Set 1 (Practice Blocks 1-8)	*2*- and *3*-Back	Set 2 (Practice Blocks 9-16)	Practice Blocks 17-20
NCD-Gap	Gates instruction and Set 1 (Practice Blocks 1-8)	Binaural beats	Set 2 (Practice Blocks 9-16)	Practice Blocks 17-20
NoGap-CD[a] - - - - - - - NoGap-NCD	*2*- and *3*-Back - - - - - - - - - - - - Binaural beats	Gates instruction and Set 1 (Practice Blocks 1-8)	Set 2 (Practice Blocks 9-16)	Practice Blocks 17-20

Note. CD = cognitively demanding; NCD = noncognitively demanding. [a]The horizontal dashed line separates the two groups that were considered likely to be (and were) combined.

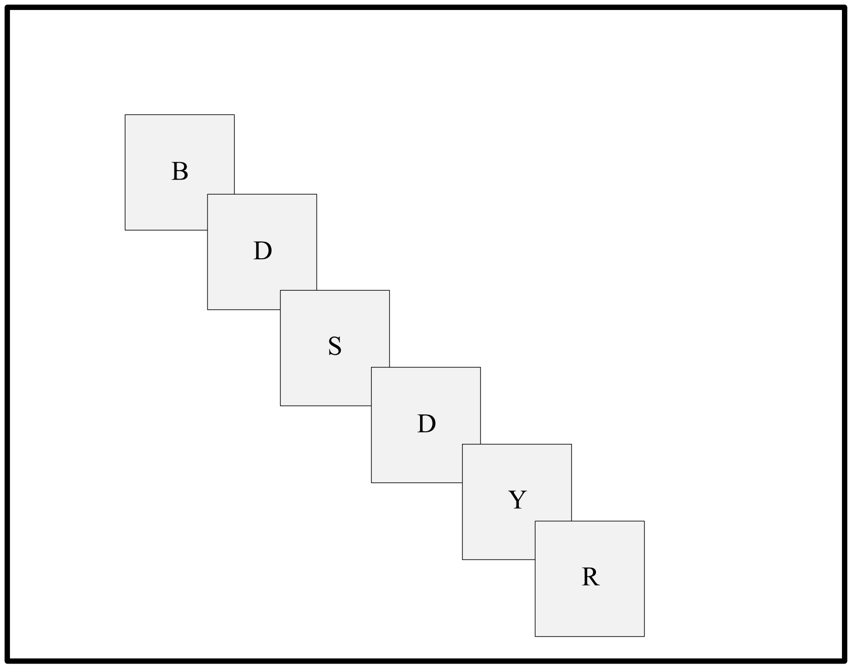

Figure 5.1. Sample series of six separate trials at the *2*-Back level.

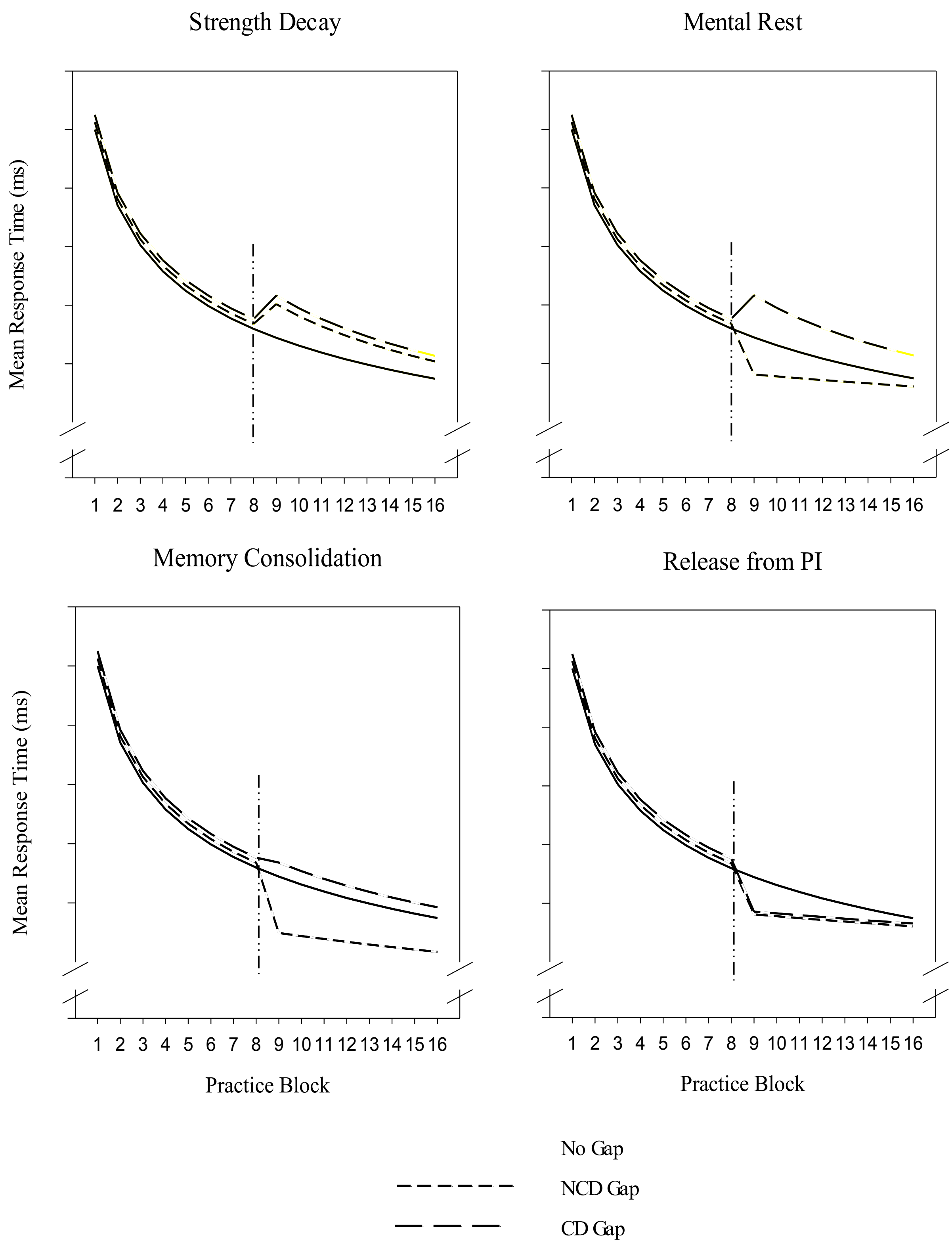

Figure 5.2. Four hypothesized result patterns. CD = Cognitively demanding; NCD = noncognitively demanding; PI = proactive interference. Vertical line indicates insertion of the interpolated task after Block 8 for the two Gap conditions.

CHAPTER 6

RESULTS

Accuracy and RT for correct responses in the learning task, as well as self-report fatigue ratings of the entire experimental session, were collected from the final sample of 140 participants for Session 1. Of these, 136 returned between 6 and 8 days later for a check of retention.

Gap Tasks

Error data were analyzed from the two experimental groups that performed the *N*-Back WM task either before or during a break in procedural learning. No group differences in error rate (M = 11.8%, SD = 5.7 and M = 11.9%, SD = 6.4, respectively) were found based on task order, $F(1,68) < 1$. Nonetheless, participants committed significantly more errors during the *3*-Back portion (M = 13.8%, SD = 6.2) than during the *2*-Back portion (M = 10.0%, SD = 8.3), $F(1,68) = 14.97$, $p < .001$, $\eta^2_p = .18$, regardless of the temporal placement of this gap activity, $F(1,68) = 1.85$, $p = .178$. This finding attests to the graduated difficulty level as N increases in the *N*-Back task. Moreover, *N*-Back error scores were positively correlated with initial procedural learning RT, as expressed in the a parameter, for both those whose WM was taxed before (CD-NoGap group, $r(33) = .383$, $p = .023$) and during a break in (CD-Gap group, $r(33) = .407$, $p = .015$) the procedural learning practice blocks. Thus, those who performed better on the *N*-Back task also began the logic gates portion of the experiment with faster responses. N-Back performance did not have a statistically significant correlation with other power function parameters. No data were collected during the binaural beats gap activity.

The main question of interest in the fatigue data was whether, as per the design, participants who experienced the *N*-Back task (CD) would rate their gap period (between Time 2 and Time 3) as more tiring than participants who listened to binaural beats (NCD) during the same period. Figure 6.1 depicts the group differences that lend support to the notion that the manipulation achieved the desired effect. Significant differences between the CD and NCD groups were observed, $F(1, 137) = 8.441$, $p = .004$, $\eta^2_p = .06$. Perhaps more importantly, there was a strong interaction between time and gap activity, for those who had their break before any logic gates learning, $F(1, 68) = 30.201$, $p < .001$, $\eta^2_p = .17$, or between Blocks 8 and 9, $F(1, 68) = 56.957$, $p < .001$, $\eta^2_p = .46$. As seen in both panels of Figure 6.1, the groups performing the *N*-Back task reported an increase in fatigue from the break activity, and the groups listening to binaural beats reported slightly less fatigue.

Learning Task

As noted previously, data from 140 participants ($N = 35$ per group) were included in the final analysis after 32 of the original 172 participants (18.6%) were disqualified due to high error rate and/or poor fit to the power function model in Set 1. Exclusions were distributed equally across the four experimental groups as follows: CD-Gap group = 8; NCD-Gap group = 7; CD-NoGap group = 10; and NCD-NoGap group = 7, $\chi^2(3, N = 172) = .597$, $p = .897$.

To determine whether participants learned to correctly solve logic gates items, error rates during procedural learning were computed. Overall errors did not differ between groups, $F(3, 136) < 1$, and were low (M = 2.5%, SD = 1.7) after 16 participants who committed over 20% errors (M = 37.9%, SD = 8.5) were eliminated. Given the exceedingly low error rate of the majority of participants, and the fact that chance accuracy was 50%, committing more than 20% errors was extreme. In addition, high error rates were generally associated with atypically fast responses that resulted in unrealistic power function parameter estimates.

The parameter estimates (*a*, *b*, *m*, and *b2*) derived from fitting each individual participant's RT data to the modified power function were the primary measures by which the hypotheses of this experiment were tested. Under the assumption that procedural learning could be inferred if and only if an individual's data fit this model, it was deemed imperative to include only participants whose performance during initial practice (Blocks 1 through 8) was reasonably well represented by the power function. As such, disqualification of any participant was based solely on error and model fit data extracted prior to the gap manipulation and any evaluation of the hypotheses. I computed R^2 as the index of model fit for each person's data during Set 1 and disqualified 16 participants whose $R^2 < .25$ (above and beyond those with error rates > 20%). The average model fit of these 16 participants was $R^2 = .097$compared to the average Set 1 $R^2 = .614$ of the remaining 140 subjects. For 6 of the 16, the model was entirely inappropriate ($R^2 = 0$). The decision to eliminate these participants with poor model fits reflected the assumption that parameter estimates extracted from data which bear little resemblance to the model would be meaningless.

Described in detail in the next section, the primary analyses of these experimental data involved not aggregate comparisons but contrasts of individual participants' parameter estimates. That said, averaged group RT are depicted in Figure 6.2 because they provide a holistic sense of the course of learning for all participants subjected to each experimental condition. The plot serves as a gauge for determining at a glance how well the obtained results may or may not conform to any one of the four hypothesized result patterns. Note that, inasmuch as the two NoGap groups did not differ in any of the parameters (see following), they are combined in Figure 6.2.

Power Function Model

Parameter estimates *a*, *b*, *m*, and *b2* were derived from individual data sets of 48 values per participant. Each value represented the mean block RT for correct responses to 16 first, second, or third gates in a given block. Means were computed after trimming outlying RT values for individual responses within a block. Because the variability of trial RT within participants showed a strong tendency to decrease with practice, a gradually decreasing criterion for trimming was implemented based on each individual's standard error of estimate (from standard error * +/- 5.5 in Block 1 to standard error * +/- 2.5 in Blocks 9 through 16). The goal was to include all but the most extreme data points. On average, 10 out of 768 total data points were eliminated per subject.

Individual model fits were estimated with the SPSS nonlinear regression procedure using a three-step process:

1. A two-parameter model (comparable to Equation 1, p. 8) was estimated for the first eight practice blocks (Set 1) only. This first step derived a measure of initial performance level *a* and nonlinear rate of change *b*.

$$RT = a * (\text{Block})^{-b} \qquad [4]$$

2. Gap change *m* was next estimated after previously derived *a* and *b* values were inserted into the second model (compare Equation 2, p. 27). Importantly, for this step all 16 practice blocks were included, with Set coded as 0 and 1 for Blocks 1-8 and 9-16, respectively.

$$RT = a * (\text{Block} + m * \text{Set})^{-b} \qquad [5]$$

3. Finally, derived *a*, *b,* and *m* values were inserted into the complete model (compare Equation 3, p. 36) to estimate the final parameter *b*2. This parameter only affects Blocks 9-16 (again, Set is coded as 0 for Blocks 1 through 8 and as 1 for Blocks 9 through 16). It sums with learning rate *b* and was included in the model to reflect any change in postbreak learning rate.

$$RT = a * (\text{Block} + (m * \text{Set}))^{(b + (b2 * \text{Set}))} \qquad [6]$$

Mean parameter estimates by group appear in Table 6.1. The values correspond generally to the learning functions seen in Figure 6.2 and thus afford a cross-check of the representativeness of both the parameter estimates and the plot. For example, mean parameter *a* values approximate RT in Block 1. As can be seen in Table 6.1, the *a* values differ little by condition. As such, the depiction of *a* in Figure 6.2 shows three lines clustered together near the same point as learning begins. Mean *b* parameter values reflect the nonlinear rate of improvement, with larger negative values indicating faster learning. Also notable in Table 6.1 and Figure 6.2, the rate of improvement did not differ substantially between conditions. Mean *m* values reflect an increment in the block variable corresponding to the performance level expected by power law learning. For example, note the largest mean value of 12.0 for the CD-Gap group. This value indicates that those participants gained, on average, the equivalent of 12 “blocks worth of practice” while they were not practicing. Said another way, the skill level (as determined by RT) they exhibited at Block 9 is the level they would have been expected to reach, according to their mean power law learning rate *b*, at Block 21. Finally, mean *b2* values reflect an adjustment to learning rate *b* for the latter practice blocks only. All *b2* values are extremely small and positive, indicating that, according to this index, there was little slowing of the original learning rate *b*. The more positive the *b2* value, however, the more slowing being observed.

Reliability Estimates

To estimate split-half reliability for the parameter estimates, all participants' power law parameters (*a*, *b*, *LNm*, and *b2*) were recalculated separately for odd- and even-numbered trials. Parameters were estimated using the same procedure as described earlier for the nonsplit sets of data. Using the Spearman-Brown adjustment, $r_{xx'}$ for parameter a = .97, b = .79, m = .55, and $b2$ = .48. The relatively low reliability coefficients for *m* and *b2* provide support for a decision to reexamine gap change and the postbreak slope trajectory with different, more reliable variables. As will be described below, a natural log transformation of *m* values has both practical and theoretical justification, and the reliability estimate for this transformation of *m* was higher, $r_{xx'}$ = .72. Also described below, an alternative method of estimating the power function rate for Blocks 9-16 produced a more reliable index of postbreak trajectories, , $r_{xx'}$ = .80.

Tests of Parameters

For each parameter or transformed equivalent, three 1-degree of freedom planned orthogonal contrasts tested the viability of the four hypothesized result patterns depicted in Figure 5.2. In each case, the first contrast compared the Gap groups to the NoGap groups (referred to as the *Gap-NoGap* contrast), the second compared the two Gap groups, CD-Gap versus NCD-Gap (the *Gap* contrast), and the third compared the two NoGap groups, CD-NoGap versus NCD-NoGap (the *NoGap* contrast).

Parameter *a*. Given that *a* represents initial performance level in the logic gates learning task, differences in group means for this parameter would likely suggest a failure of the random assignment to equate participants in the four conditions at the outset or, alternatively, that the activities of the NoGap groups affected their initial learning performance. As recorded in Table 6.1 and depicted in Figure 6.2, no preexisting differences in *a* were expected or found when group means were compared via the three contrasts: Gap-NoGap, $F(1, 136) = .13$, $p = .721$; Gap, $F(1, 136) < 1$; and NoGap, $F(1, 136) = < 1$.

Parameter *b*. Statistically significant mean differences between groups on parameter *b* would be indicative of diverse rates of skill acquisition in the logic gates task. As with parameter *a*, however, the means of parameter *b* were similar across the four groups, according to the three contrasts [all $F(1, 136) < 1$]. Because the two groups that experienced no break between Blocks 8 and 9 (i.e., the NoGap groups) did not differ as to their *a* and *b* parameters, as noted earlier, their data are depicted by a single line in Figure 6.2. This merging of NoGap groups was anticipated and facilitates juxtaposing this figure showing observed performance with the hypothetical result patterns displayed in Figure 5.2. Furthermore, the equivalence of *a* and *b* parameters for Gap and NoGap groups allowed for hypotheses about *m* and *b2* parameter differences to be tested without consideration for initial learning differences due to gap task placement in the session.

Parameter *m*. Gap effects, encapsulated by *m* and conceptualized in the metric of block, are interpreted as facilitative when *m* values are positive and detrimental when *m* values are negative. Statistical tests of group differences in the magnitude and/or direction of gap change estimator *m* were evaluated against the predictions of the four hypothesized result patterns. The two predictions depicted in Figure 5.2 that most resemble the actual mean learning curves are those of memory consolidation and release from PI. Accordingly, the Gap-NoGap and Gap contrasts were most instrumental in distinguishing between these explanations. The consolidation hypothesis predicted a significant Gap contrast; the release from PI hypothesis predicted a nonsignificant Gap contrast but a significant Gap-NoGap contrast.

In order to accurately test the significance of the contrasts for parameter *m*, a natural log transformation was performed on the estimated values. This was done in part to reduce a strong positive skew in the distribution, and, as reported earlier, the reliability of log transformed *m* was markedly better than that for *m*. Equally important, logarithmic transformations are used routinely when statistical analyses involve the power function; indeed, in their seminal article from 1981, Newell and Rosenbloom use the phrases *log-log linear learning law* and the *power law of practice* interchangeably. Means and confidence intervals for *LNm* are shown in Figure 6.3. Significant mean differences were evidenced for *LNm* values with the Gap-NoGap contrast, $F(1, 136) = 15.47$, $p < .001$, $\eta^2_p = .10$, but not with the Gap contrast, $F(1, 136) = 1.09$, p = .299, or the NoGap contrast, $F(1, 136) = 2.02$, p = .157. [Incidentally, when the contrasts were tested with the (untransformed) *m* parameter estimates, the same conclusions were drawn: Gap-NoGap contrast, $F(1, 136) = 8.56$, $p = .004$, $\eta^2_p = .061$; Gap contrast, $F(1, 136) = 1$, $p = .32$;

NoGap contrast, $F(1, 136) = 1.56$, $p = .214$.]

As shown in Figure 6.3, the two Gap groups' large *LNm* scores relative to those of the NoGap groups, regardless of which gap activity they participated in, suggest that simply switching to a different task for 15 min after Set 1 brought about faster RT in Block 9; the mental effort demanded during the interpolated task did not seem to matter. This conforms well with predictions by the release from PI explanation. Meanwhile, the comparatively small *LNm* scores of the NoGap groups conform with the incremental, gradually asymptoting improvement predicted by the power function under conditions of uninterrupted practice.

Set 2 learning rate. The *b2* parameter serves as an adjustment to learning rate *b* during postbreak Practice Blocks 9-16, or Set 2. As was the case with the *LNm* parameter, the Gap-NoGap and Gap contrasts were most useful with *b2* for distinguishing between consolidation and release from PI predictions. The consolidation explanation predicts no difference in slowing with respect to either contrast, whereas the release from PI explanation predicts significantly more slowing for Gap compared to NoGap groups, and no difference between Gap groups. No differences between any of the groups were found when the *b2* parameter was tested in accordance with the three planned contrasts: Gap-NoGap, $F(1, 136) = 1.96$, $p = .164$; Gap, $F(1, 136) = 1.74$, $p = .189$; and NoGap, $F(1, 136) = < 1$.

The result of this statistical analysis of *b2* was surprising given the appearance of the Set 2 learning curves in Figure 6.2. This, along with low reliability estimate reported earlier, brought into question the utility of this parameter as the primary index of Set 2 learning rate adjustment. Consequently, to evaluate participants' performance during the second half of their learning experience, I conducted a post-hoc analysis in which the slope of Blocks 9 through 16 was computed in log-log coordinates. The transformed variable, *Set2b*, is useful because the linear slope computed from the log of RT regressed on the log of Block represents the rate parameter of the power function. As such, the individual values of *Set2b* can be conceptualized as, and contrasted with, the *b* learning rate parameter, but representing Set 2 learning. The *Set2b* index allows for testing performance trends in Blocks 9 through 16 with a power function metric, and, in contrast to the *b2* parameter, it is estimated independently of the other three parameters in the modified power function.

Reexamination of Set 2 data using the post hoc *Set2b* variable aligned more closely with the learning curve trajectories depicted in Figure 6.2. Respective means and confidence intervals are shown in Figure 6.4, and, for comparison purposes, means and confidence intervals for *b* parameter estimates reported earlier are also shown. Once again, the *b* parameter reflects the learning rate estimated for Blocks 1 through 8 only and was never compared statistically to the *Set2b* parameter, though they appear on the same plot. As such, when interpreting Figure 6.4, note that the more similar the *b* and *Set2b* mean values within any group, the less the learning rate changed in the later blocks.

When analyzed with the three orthogonal contrasts, significant *Set2b* Gap-NoGap differences were found, $F(1, 136) = 47.43$, $p < .001$, $\eta^2_p = .26$. As is evident in Figure 6.4, the Gap groups both slowed considerably, failing to sustain the dramatic RT reductions they realized immediately after their breaks. In addition, these two groups' patterns of slowing differed from each other, $F(1, 136) = 16.12$, $p < .001$, $\eta^2_p = .11$, though the effect size was small. This difference was not predicted by the release from

PI explanation. The NoGap groups did not differ as they maintained their power function-shaped improvement after Block 9, as would be expected, $F(1, 136) = 1.92$, $p = .168$.

Session 2: Retention Blocks

Participants returned 6 to 8 days after their initial learning session to be tested on their memory for logic gates rules and procedures. No review information whatsoever was given as the four retention blocks of 16 items each began. It should be noted that there were no group differences in mean RT across Blocks 13 through 16, the last four blocks of practice prior to the week-long retention interval, $F(3, 136) < 1$, allowing for a straightforward interpretation of the retention results.

The comparison of primary theoretical interest at retention was the Gap contrast. Under the memory consolidation hypothesis, this comparison would have been significant in favor of the NCD group due to the stabilization of their learning during the wakeful resting period. The Gap-NoGap contrast was also potentially informative because it compares groups receiving spaced practice in Session 1 (both Gap groups) with groups receiving massed practice (both NoGap groups). Though this research was not designed to test the well-established spacing effect (for reviews, see Cepeda, Pashler, Vul, Wixted, & Rohrer, 2006; Dempster, 1988), the format aligns closely with a typical description of just such an investigation: “A spacing experiment should involve multiple periods of study devoted to the same material, separated by some variable time gap, with a final memory test administered after an additional retention interval measured from the second exposure” (Cepeda, Vul, Rohrer, Wixted, & Pashler, 2008, p. 1095). As such, results of a group comparison of mean accuracy and latency scores would be predicted to favor the Gap groups.

Figure 6.5 presents means for both RT and errors by condition for the retention session. All groups can be seen to have retained the logic gates production rules in memory extremely well. Overall mean error rates were low and similar across conditions, with no differences found according to the Gap-NoGap contrast, $F(1, 132) = 1.4$, $p = .239$; the Gap contrast, $F(1, 132) = 2.49$, $p = .117$; or the NoGap contrast, $F(1, 132) < 1$. With regard to latency, the contrast of both initial RT performance (*Ret-a*) and the linear slope of RT (*Ret-b*) for Blocks 17, 18, 19, and 20 were computed in log-log coordinates. As with the error data, overall mean RT across conditions indicated that all groups retained the logic gates skill at a high level. No group differences were found according to any of the contrasts either for *Ret-a* or for *Ret-b*, [all $F(1, 132) < 1$ except the NoGap contrast, $F(1, 132) = 1.6$, $p = .207$].

It is important to note that, although participants in this study failed to exhibit a decrement to their performance after either interpolated activity during Session 1, they did so upon returning for Session 2 one week later. The scallop up in RT at the 17th practice block (Block 1 in Figure 6.5) is evidence of the decay theorized to occur over longer lags in skill learning architectures such as ACT-R (Anderson, 1993). However, after just one retention block, all groups' mean RT approximated that of the final practice blocks in Session 1. This rapid recovery from warm-up decrement observed after the lengthier break between practice sessions is similar to that noted in other studies of cognitive skill acquisition (e.g., Anderson et al., 1999; Woltz, Gardner, & Bell, 2000).

Table 6.1

Means of Power Function Parameters and Overall Model Fit

	Parameter				
Group	*a*	*b*	*m*	*b2*	R^2
CD-Gap	1881 (754)	-.255 (.08)	12.0 (13.6)	.00317 (.0036)	.74 (.11)
NCD-Gap	1861 (872)	-.274 (.08)	9.1 (12.9)	.00180 (.0037)	.79 (.09)
CD-NoGap	1785 (663)	-.258 (.09)	2.8 (8.4)	.00111 (.0050)	.68 (.15)
NCD-NoGap	1868 (680)	-.268 (.10)	6.4 (12.9)	.00180 (.0049)	.73 (.12)

Note. Standard deviations are in parentheses. *a* = initial performance level; *b* = learning rate; *m* = gap change; *b2* = postgap trajectory; CD = cognitively demanding; NCD = noncognitively demanding.

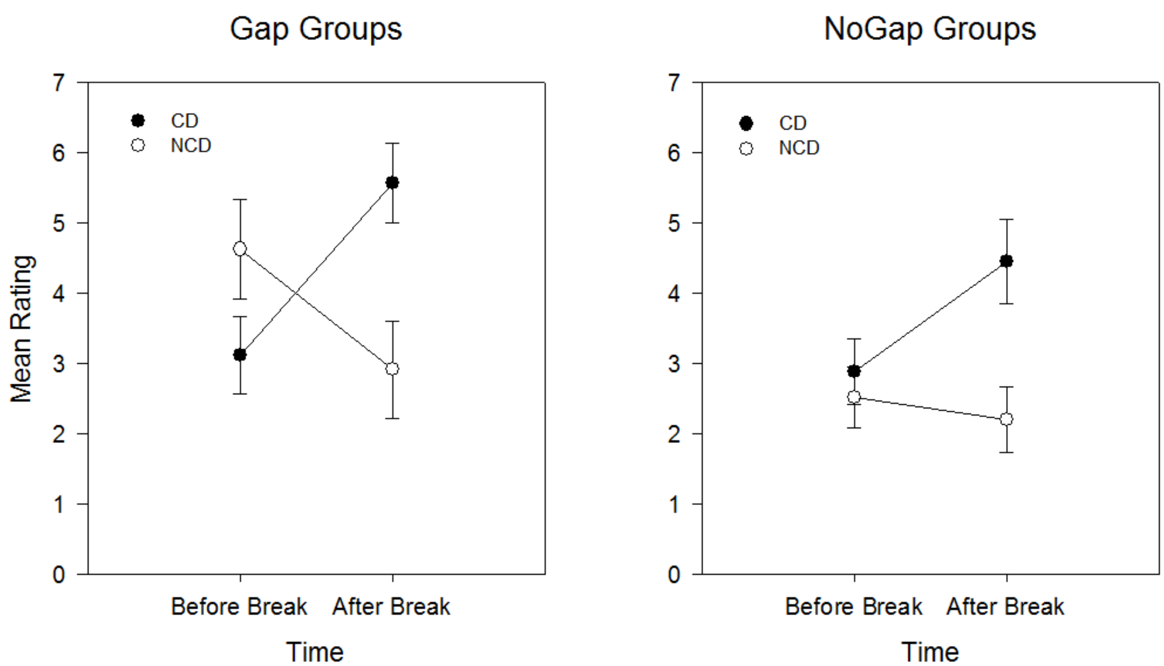

Figure 6.1. Mean self-reported fatigue ratings of gap activity by group and temporal placement of break.

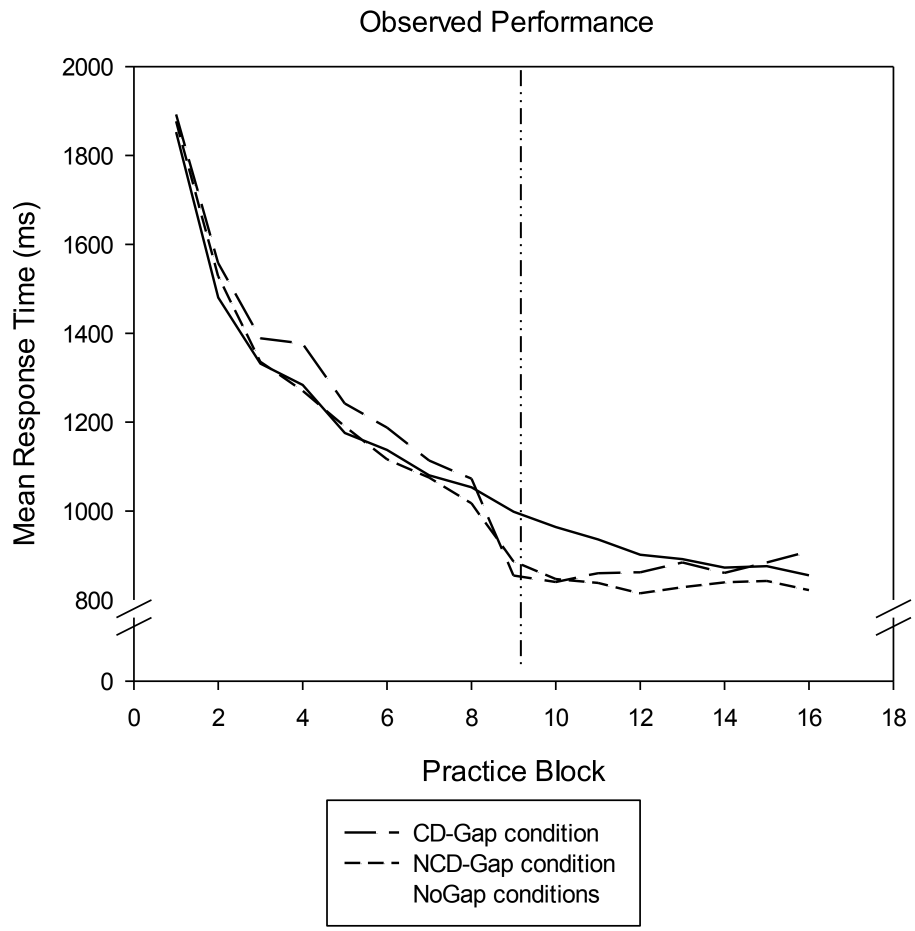

Figure 6.2. Learning curves of the two Gap groups and combined NoGap groups. CD = cognitively demanding; NCD = noncognitively demanding. Vertical line indicates insertion of the gap task after Block 8 for the two Gap conditions. NoGap groups experienced the gap tasks before Block 1.

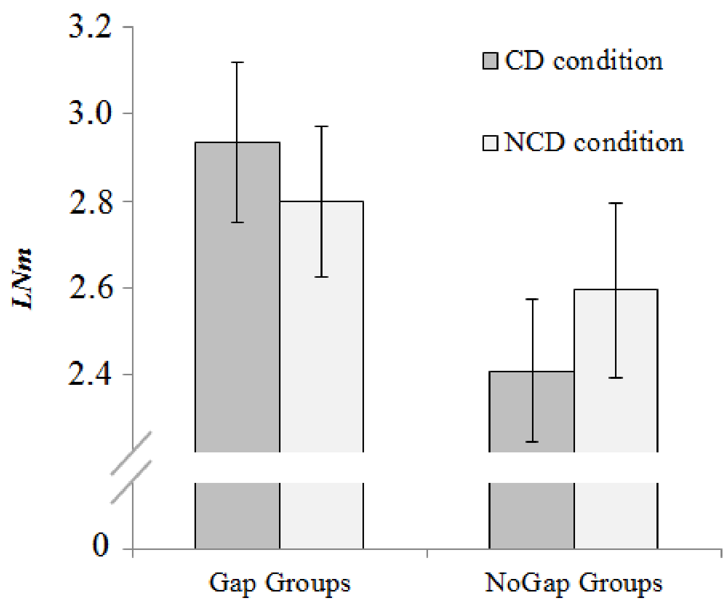

Figure 6.3. Means (with 95% confidence intervals) of transformed gap change parameter *m*. *LNm* = log of *m* parameter; CD = cognitively demanding; NCD = noncognitively demanding.

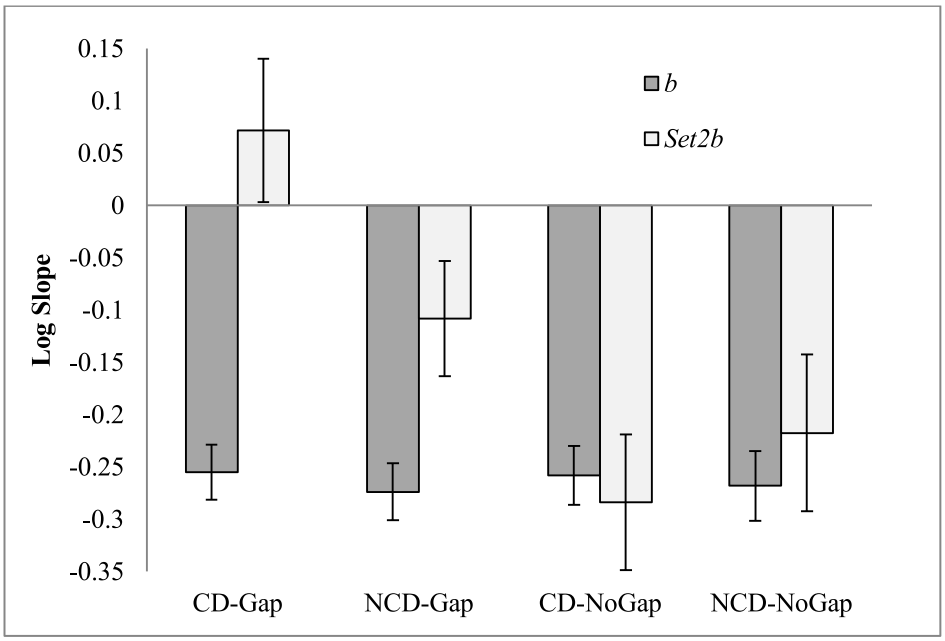

Figure 6.4. Means (with 95% confidence intervals) of transformed learning rate parameters. *b* = learning rate; *Set2b* = log of linear slope from Blocks 9 through 16; CD = cognitively demanding; NCD = noncognitively demanding.

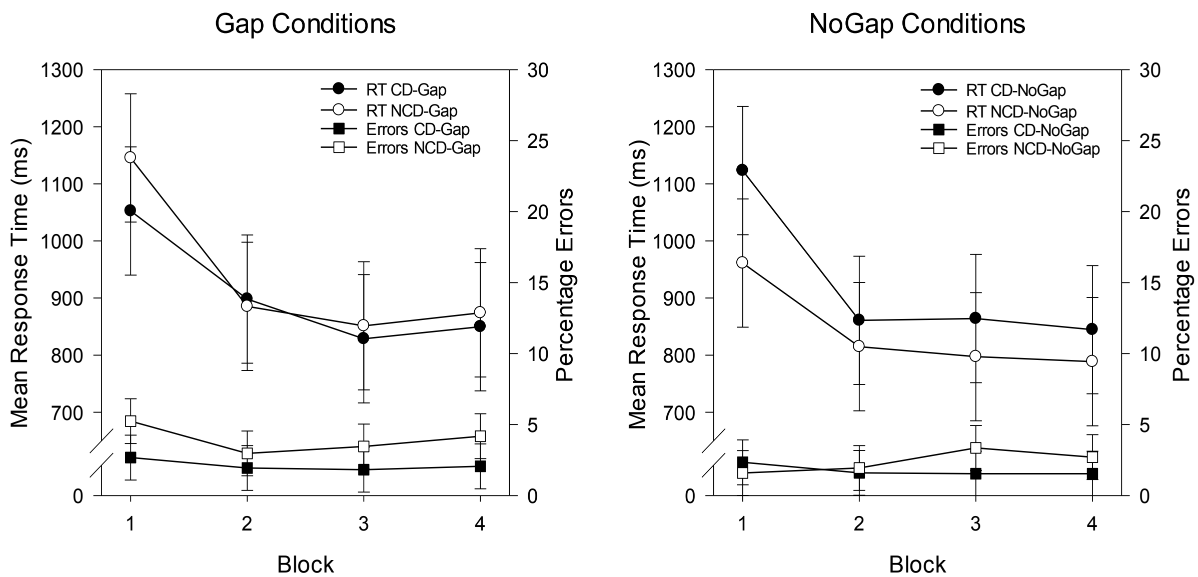

Figure 6.5. Means (with 95% confidence intervals) for Retention Blocks 17-20. CD = cognitively demanding; NCD = noncognitively demanding.

CHAPTER 7

DISCUSSION

Based on the nature and temporal placement of two distinct gap tasks, the present experiment investigated three explanations for predicted skill improvement during a break in skill practice, or gap facilitation: memory consolidation, release from PI, and mental fatigue. Specific patterns of RT change were hypothesized a priori to correspond to the explanations for gap effects (see Figure 5.2), and facilitation was indeed observed in both groups who briefly interrupted the course of their skill practice, and to an indistinguishable degree. After statistically analyzing data with three planned contrasts that reflected prediction differences, the results support the theoretical view that release from PI was primarily responsible for the gap improvement. Each of the explanations will presently be addressed in light of the observed experimental outcomes.

Tests of the Four Hypothesized Result Patterns

Strength Decay

The results were not consistent with forgetting as an explanation for observed performance following a within-session break for the two Gap groups. According to Anderson's (1993) ACT-R theory that incorporates power law learning, memory strength for to-be-learned material decreases during periods of nonpractice. Inasmuch as both Gap groups disengaged from the same learning task for the same amount of time after the same eight blocks of practice (i.e., during Set 1), both would have undergone the same amount of forgetting during the break, regardless of the character of their break activity. Forgetting would have been manifested in higher (i.e., worse) initial postbreak RT and negative *m* parameters for both groups. This was not the case with the short-term test performed here. All *m* parameter estimates were positive, disqualifying strength decay as accounting for observed performance by any of the participants. Nevertheless, though this finding disconfirms memory strength decay as a mechanism affecting skill acquisition during relatively brief breaks from practice, evidence of performance decrements from delays over 1 day (as between Blocks 16 and 17, in this study) supports the importance of this mechanism for longer time intervals (Anderson et al., 1999). It is possible that, in the case of cognitive skill learning, decay effects require a longer period of time offline to affect the strength of recently acquired procedural learning productions.

Mental Rest

Under this explanation, participants in the two Gap groups should have exhibited opposite performance patterns at Block 9. Those in the NCD-Gap group should have seen a drop in RT due to experiencing a period of mental quietude after Block 8, and those in the CD-Gap group should have seen a rise in RT due to experiencing a period of fatigue-producing mental effort. While it is true that the NCD-Gap participants' RT showed a marked decline following the break, the CD-Gap group showed an equally dramatic decline upon resumption of trio practice. These findings disqualify mental rest as an explanation for the current gap effects. However, the possibility remains that a general mechanism of mental rest could be instrumental in extensive practice of more demanding cognitive skills.

Memory Consolidation

Neither of the two outcomes deemed suggestive a priori of providing evidence for the memory consolidation explanation came to fruition. The first necessary outcome was that only the NCD-Gap group should experience gap facilitation; the second was that the postbreak learning rate (as estimated by the *Set2b* parameter) of said group should be comparable to its prebreak rate (described by parameter *b*.) Actual results were quite to the contrary. Both Gap groups experienced gap facilitation, and neither Gap group resumed its prebreak learning rate. These findings eliminate memory consolidation as a possible explanation for gap facilitation following a relatively short break in the practice of this skill.

Release from PI

The observed outcomes comport with release from PI as the explanation for gap facilitation. Both the CD-Gap and NCD-Gap groups demonstrated increased skill (as indicated by their relatively large, positive *LNm* values) after their gap activities, as was predicted under this explanation. The magnitude of initial improvement was also temporary, which fits with the characteristic of procedural PI to accumulate anew with resumption of the same activity which had precipitated its initial occurrence. The Set 2 learning rate for both Gap groups was slower than that for both NoGap groups. The comparative trajectory of the Gap groups' postbreak learning was less well predicted, however. Both Gap groups were expected to behave identically during Set 2, but RT increased at a faster rate for participants who endured the effortful break activity. This is difficult to reconcile with a simple release from PI model. It raises the possibility that residual mental fatigue from the CD break activity played a role in general performance declines or even the susceptibility of participants to PI.

Implications of the Findings

These results hold implications for at least four issues related to cognitive skill acquisition, each of which will be addressed in turn. First, in finding that temporarily discontinuing practice of a nascent cognitive skill did not thwart immediate postbreak skill performance, the outcome mirrors similar but limited findings from the motor domain and may constitute an exception condition to the power law of practice and the expected detrimental effect of time (Anderson et al., 1999). Second, failure to find significant differences in the magnitude of gap facilitation between the CD- and NCD-Gap groups, despite the dissimilarity of their break tasks, must be reconciled with recent empirical evidence for offline memory consolidation during periods of wakefulness. Third, the release from PI that appears to have been instrumental in these experimental results should be conceptualized as a distinctly procedural memory phenomenon, as opposed to the notion of PI typically embodied in verbal learning research. Finally, engaging in a 15-min break had a detrimental effect on the postbreak learning trajectory of subjects in the Gap groups, their prior gap facilitation effects notwithstanding. These results prompt questions as to whether interrupting the practice session of the Gap groups in pursuit of offline learning was worth it, especially considering that subjects across all groups performed with a high degree of accuracy, and indistinguishable latencies, on their four-block retention test 1 week later.

Implications Related to Power Law Learning

The observation of enhanced procedural skill performance following a stoppage of practice in this experiment is consistent with results from the pilot study. The finding is not consistent, however, with a well-established tenet of the power law of practice, articulated succinctly by Anderson and Schunn (2000) with respect to the ACT-R theory: "…performance continuously improves with practice and continuously degrades with…time" (p. 12).

Anderson's (1993) skill acquisition theory may be applied to the procedural learning exhibited in the present experiment. As participants engaged in continuous practice of logic gates trio items (i.e., A-O-O, A-A-O, O-A-A, and O-O-A sequences), the component productions which were repeatedly encountered would be expected to grow in strength, making them easier to access and more resistant to forgetting. After spending time offline during their break, Gap group participants' latencies would be expected to increase as a function of the decrease in production strength associated with a period of nonpractice. Such longer latencies would appear as perceptible scallops up in the learning curve (for an example over 24-hour delays, see Anderson et al., 1999). However, engaging in a 15-min diversionary activity after Block 8 not only failed to immediately degrade these participants' performance, but average RT improved significantly thereafter. Participants solved logic gates trios during Block 9—immediately after their break—as quickly as their individual power function model estimates predicted they would at Block 18. In effect, they advanced themselves a substantial 10 blocks of practice by taking a break. This result stands in stark contrast to the performance decrement predicted to occur under such a circumstance.

Examples of exceptions to continuous power function-shaped learning are relatively scarce in the literature but are not without precedent. A flurry of research in the mid-20th century incorporated the pursuit rotor learning task to investigate motor skill development and regularly demonstrated reminiscence, as indicated by within-session performance improvements apart from practice. Gains were primarily attributed to reduction of temporary work decrement (e.g., Ammons, 1947), dissipation of inhibitory potentials (e.g., Hull, 1943; Kimble, 1949), and extinguished conditioned inhibition in massed-then-spaced practice (e.g., Denny, Frisbey, & Weaver, 1955). More recently, Hotermans et al. (2006) observed a transient boost in finger-tapping performance in certain of their experimental groups that were tested at various intervals (e.g., 5 min, 30 min, 4 hr, 24 hr) after the end of a practice session. No indication was given as to what activities participants engaged in during the retention interval, but this research team of neuropsychologists speculated that the short-term improvement reflected a temporary postpractice period during which motor memory was activated.

The foregoing short list of exceptions to uninterrupted power law learning is surely not exhaustive but does serve to demonstrate the veracity of Robertson, Pascual-Leone, and Miall's (2004) observation that few procedural tasks have demonstrated offline performance improvement, especially after wakeful periods. These authors further note that skill improvement without practice cannot be considered a general feature of motor learning, specifically, until a greater variety of procedural tasks are tested.

Another implication of the results of this study for power law learning addresses challenges to the very use of the word "law" in association with learning curves well fitted by the power function. Although Newell and Rosenbloom's (1981) basic premise—that learning through practice is most often best described by the power function—has been widely adopted (Logan, 1992), there are dissenters. Heathcote, Brown, and Mewhort (2000) "repealed" the power law, declaring that evidence in support of using the power function is flawed because it relies almost universally on fits to averaged data. To make their case that the exponential function in general (and their APEX version, in particular) should instead be the default option for describing skilled performance, they fit a variety of functions to data representing over 7,910 individual learning series from 475 separate subjects. They found the exponential function to provide a better fit in 82.2% of cases and to account for a greater proportion of the variance in every case. Among the reasons cited for these findings are two that may be relevant here: first, the power function's hyperbolically decreasing learning rate parameter is inaccurate compared with the exponential function's constant estimation of the learning rate; second, the power function has a tendency to underestimate the asymptote and, consequently, produce a bias in its favor.

To check their assertion that the exponential function is superior to the power function for fitting individual data, I calculated a model fit for each participant for the two-parameter power function, $T = BN^{-\alpha}$, and for the two-parameter exponential function, $T = Be^{-\alpha N}$, both as delineated by Newell and Rosenbloom (1981). This was accomplished using the same 48-value individual data sets as were employed earlier to estimate the subsequently contrasted parameters, but only after performing a log transformation of each RT. The log RT-log block linear relationship was estimated for the power function and the log RT-block for the exponential function. The average R^2 was .69 for the power function and .61 for the exponential function, with the power function providing a superior description of individual logic gates learning curves for 92% of participants.

This outcome is in contrast to the analyses reported by Heathcote et al. (2000) for fitting individuals' learning curves. One reason for this discrepancy could lie in the correspondence between the fundamental shape properties of the two functions in question and specific learning tasks. A visual comparison of prototypes of both the power and exponential functions reveals the power function to have a steeper initial slope and a quicker flattening of the performance curve as blocks progress relative to the exponential function. Describing the variation in the algorithms that precipitates this fundamental shape difference, Heathcote et al. (2000) noted that "the defining characteristic of an exponential function is a constant RLR (relative learning rate, notated α) at all levels of practice. For the general power function, by contrast, RLR is a hyperbolically decreasing function of practice trials" (p. 187). This difference in the way the two functions derive the learning rate parameter (designated as b herein) may be especially germane to the present case. Throughout the procedural learning portion, participants were repeatedly confronted with binary-choice response items that were highly similar (i.e., 0,1 inputs encased in either brackets or parens), presented at a unrelenting pace ($M \approx 1.15$ sec/gate) and with infrequent feedback. The average participant solved trios of such items continuously for approximately 15 min per Set, presumably ample time for PI from highly similar items to amass and retard the learning process.

To the extent that the foregoing accurately describes a typical participant's experience in the present experiment, the steep-then-asymptotic character of power curves may provide the better match to actual performance because rapidly building interference prevents the steady, more gradual slowing of RT described by Heathcote et al. (2000) as definitional to the exponential function. On the other hand, with tasks that by nature take longer to perform (such as solving geometry proofs), have a greater variety of item content, are slower in pace, or are regularly broken up with new instructions or feedback, interference may present less of a threat. In these cases, the slightly gentler slowing inherent to the exponential function may better describe the learning curve. This possible explanation of power versus exponential function fits to individual learning data as a function of PI will be addressed subsequently in future research directions.

Implications Related to Memory Consolidation Processes

The outcomes of this study suggest that memory representations for the productions associated with the logic gates procedural skill did not undergo memory consolidation as the NCD-Gap participants listened to binaural beats. This finding is somewhat surprising in light of recent perceptual-motor evidence described by neuropsychologists (e.g., Carr et al., 2011; Karni & Sagi, 1993; Muellbacher et al., 2002; Walker, 2005). With animals as subjects, these researchers observed that labile, task-related neural traces were replayed in the hippocampus during periods of immobility or brief pauses in (usually maze) exploration. They hypothesized the level of reactivation to be “a potential contributor to both consolidation and retrieval” (p. 147) because newly learned memory patterns were found to be correlated with subsequent performance on a related memory task. Given this evidence, it seemed plausible in the present experiment that nascent neural traces of logic gates productions in NCD-Gap participants might similarly replay during their brief rest. If consolidation reflecting hippocampal replay did occur to a meaningful extent during the binaural beats break, the behavioral measure of learning used here was not sensitive enough to detect evidence of reinforced circuits.

It is possible that memory consolidation was not observed in this experiment due to my choice of gap activities. Both gap tasks, binaural beats and *N*-Back, were chosen specifically for their potential to elicit (or not) immediate-onset memory consolidation effects, if there were to be any. Based in large part on the verbal memory studies of Dewar et al. (2009, 2012), the presumption was that memory consolidation processes would commence "when the time that follows new learning is devoid of further stimuli" (2009; p. 627), akin to the brief pauses associated with hippocampal replay. The binaural beats break task was supposed to provide as close an approximation of a stimuli-free environment as possible, given the constraints of a multisubject lab setting: limited external visual stimulation (due to the wearing of dark goggles); continuous presentation of neutral, purportedly alpha brain-wave-entraining auditory input through headphones; and physical relaxation (head down on the desk). In the Dewar et al. (2012) version of the restful break, elderly participants sat alone in a dark, quiet room after hearing one of two short stories.[2]

The result of the Dewar et al. (2012) subjects' 10-min rest break was better recall of story units when a passage was followed by a 10-min rest period versus a stimuli-filled break activity (a *Spot-the-Differences* visual detection task). Even more impressive, the superior recall persisted when participants were retested 1 week later. These authors attributed the long-term memory enhancement to a consolidation process that began

[2] Example of the contents of a short story participants in the study by Dewar et al. (2012) heard: *Anna Thompson of South Boston, employed as a cook in a school cafeteria, reported at the police station that she had been held up on State Street the night before and robbed of $56.00. She had four small children, the rent was due, and they had not eaten for two days. The police, touched by the woman's story, took up a collection for her*. (Wechsler, 1997)

immediately after encoding and that was fostered by the participants' interference-free mental environment at the time. One does wonder, however, if participants thought about the most recent story at least a little bit during their wakeful resting break. The context of the entire experience for these older subjects was a memory study, after all. Only 3 of 14 (21%) admitted to having done so in the Dewar et al. postsession interview; nonetheless, it is difficult to rule out the possibility that some amount of covert rehearsal of the story units took place in that solitary, silent environment immediately following the presentation of a story.

Another possible reason for the failure to find evidence of memory consolidation in the present experiment could be that my choice of the binaural beats break task was simply a poor one for inducing restfulness, that the quiet room manipulation more effectively produced an interference-free mental environment. That said, participants in this experiment did indicate in their end-of-session self-report fatigue ratings that they felt less fatigued after the NCD break than they felt prior to it. Nonetheless, they may have devoted attentional resources, either inside or outside of awareness, to the novel, pulsating sounds, the discomfort of the lab chair, their upcoming exam in a difficult class, or a host of other distractions rather than letting their minds wander freely. It is also possible that my choice of wavelength was incorrect. I chose alpha beats because they supposedly stimulate the brain waves associated with relaxation, but perhaps gamma, delta, theta, or beta waves would have been better at eliciting a restful subconscious state in the listeners. It is further possible that alpha beats were the appropriate choice but that the expected entrainment failed to occur for some reason. This should not have mattered, though. Quiet listening should have been much more relaxing than engaging in the *2*-

and *3*-Back task during the gap, regardless of the beat wavelength.

Another possible explanation for the failure to find evidence of memory consolidation was the temporal length of the break. It is possible that, at 15 min, the break was too long or too short to capture the effect. This seems unlikely, however, because others have found improvements after 3 min (in an implicit SRT task; Heuer & Klein, 2003) and 5 min (in a finger-tapping task; Hotermans et al., 2006). In the latter case, the gain was also evidenced by another experimental group they did not test until 30 min later.

Finally, it should be noted that, though none of the specific studies cited as evidence supporting consolidation involved acquiring a mental skill, the commonalities between motor- and cognitive-skill domains described by Rosenbaum et al. (2001) made the possibility of a shared consolidation mechanism seem likely. It seems plausible, as well, that at least some of the prior motor evidence deemed suggestive of offline memory stabilization processes might have actually reflected the consequences of rest or release from PI, to the extent those alternative explanations were not carefully evaluated.

Implications Related to Release from PI

Release from PI appears to have been the cause of gap facilitation in this study, but the process must be considered in an atypical way to be applicable here. Most often in the cognitive literature, PI is discussed in the context of verbal, declarative memory, as when previously learned material (e.g., lists of words) disrupts one's memory for more recently learned items (Anderson & Neely, 1996). However, in procedural learning of the type participants engaged in here, theories from both the behavioral and cognitive domains can be understood to support the notion that deleterious effects of PI were a function of mere event recurrence.

According to Hull's (1951) negative drive theory, procedural learning is envisioned as habit-building, or the continual strengthening of conditioned responses that inherently involves practice, or repetition, of an activity. Concomitant with the incrementally increasing strength of a skill or habit due to ever-intensifying stimulus-response reaction potentials, however, is the inhibitory potential (also referred to as temporary work decrement by Ammons, 1947, and as reactive inhibition by Kimble, 1949) resulting from each evoked reaction. This variously named response deterrent "inhibits to a degree according to its magnitude the reaction potential *to that response*" (Hull, 1951; p. 74, italics added). In other words, repetition of an activity is accompanied by an innate drive to stop repeating the specific activity. In summary, PI due to reactive inhibition accumulates during the repetitive learning trials necessary for proceduralizing a skill. A cessation of practice allows for dissipation of the content-specific interference. Thereafter, improved performance of the skill is evidenced upon resumption of training.

From the cognitive domain, Anderson's (1983, 1993) ACT architectural framework similarly envisions procedural interference as associated with event recurrence, but the recurrence of highly similar events corresponds to overlapping condition-action productions. In this context, the lingering presence in WM of one production (or potentially more) has the potential to disrupt the performance of another production if conditions and actions are similar. *True* procedural interference, as described by Singley and Anderson (1989), is a logical consequence of a pattern matching process made more complicated due to the nature of procedural learning. A fan effect, of sorts (Anderson, 1974), occurs when a set of conditions in WM activates multiple productions and thereby lengthens the time required for any single production to be matched and, subsequently, to fire. In a similar vein, Schneider's (1987) connectionist/control architecture predicts PI to build—and thereafter slow learning—as a result of the concurrent storage of multiple patterns in a single set of connection weights. As formulated in both these cognitive architectures, the accumulation of procedural PI is theorized to be closely related to the level of similarity of the to-be-learned content and the rapidity with which it is presented.

In accordance with the previous explications, the series of events involved in the execution of each of 768 distinct gate responses (i.e., deciphering the symbols, re-instantiating the corresponding rule, determining the correct output, pressing the appropriate response key, and holding the 0 or 1 answer in WM to be incorporated into the next gate) appears to have induced a build-up of PI. Unfortunately, the only way to eliminate the interference, and the attendant slowing of RT, was to stop practicing. Or, viewed more positively, the only thing necessary to eliminate the interference was to stop practicing because the interference was content-specific. The interference built up during—indeed, because of—the execution of the logic gates task; hence, all that was necessary for interference to dissipate was the cessation of the logic gates task. The task- or content-specific nature of the accumulated inhibition is key here because it explains why both the CD and NCD groups experienced gap facilitation: both groups stopped the learning task. The diverse character of the two breaks did not differentiate postgap performance because the two groups did not vary with respect to what was requisite for release from PI to occur.

Though the results of this experiment did not support the mental rest explanation for gap facilitation effects, this mechanism may have affected the results in an unanticipated way. Had mental rest been operating during the break, the diverse quality of the two gap tasks should have differentiated the Gap groups' second-half performance. The cognitively effortful nature of the *N*-Back task should have exacerbated any fatigue the CD-Gap participants developed during Set 1 and left them feeling more worn out at its conclusion than they were when it began. It seems highly unlikely they would have performed at an $m = 12$ level during Block 9 had fatigue been operating. It is possible, however, that cognitive fatigue did take a delayed toll on these participants. Their postgap rate of learning slowed more than that of the NCD-Gap group, suggesting that perhaps by the time they were well into Set 2, their overall cognitive stamina was compromised due to the taxing nature of their experimental condition.

Finally, a potential link can be drawn between the hippocampal replay mechanism described in relation to memory consolidation and the release from PI explanation for gap facilitation. Neural researchers theorize that there is a period—especially one of quiescence—after a learning episode ceases during which newly formed memory representations are unstable and thus ripe for hippocampal replay to occur. This replay is thought to eventually result in stronger memory traces (Carr et al., 2011). The results of this experiment suggest that, concurrent with that uncluttered period, unstable, interference-laden memory representations undergo a release process from the disruptive effects of inhibitive forces that have been acting on the fragile productions (in the case of procedural learning). Perhaps hippocampal replay and release from PI can work in concert to stabilize newly acquired memory representations. This is an alternative explanation to that of fatigue for the Set 2 learning rate difference between CD-Gap and

NCD-Gap participants. It is conceivable that release from PI was instrumental in both groups as a function of suspending logic gates practice, but that only the NCD-Gap participants experienced conditions conducive to consolidation and therefore showed slower buildup of PI when practice resumed.

Limitations

The results of this experiment provided one plausible answer to a narrow question related to cognitive skill acquisition. The answer was that release from PI was the mental mechanism operating when temporary cognitive skill improvement was observed after a 15-min break in procedural practice. The question was narrow in that the conclusions drawn can only be said to apply, at least at the present time, to rapidly solved two-choice items of a moderately complex, cognitive nature that are learned declaratively first, then practiced to a high level of fluency within a 1-hour lab experiment. Thus, there are limits to the generalizability of the current findings beyond the single-session instructional regimen, the difficulty level of the learning task, the choice and timing of break activities, and the week-long retention interval, among other things.

As with most studies, this one has elicited retrospection about the specific hypotheses tested, design choices, and other basic issues. Though, as stated in the Introduction, there are probably myriad explanations for gap facilitation effects, only memory consolidation, release from PI, and mental rest were singularly conjectured here as being potentially influential. Observed skill improvement following a gap in blocks of practice may, however, reflect the combined influence of two or more mechanisms, likely resulting in outcome patterns distinct from the four described earlier. Furthermore, a targeted mechanism may actually be operating but remain undetectable due to characteristics of the experimental design.

Future Research and Contribution

One compelling question introduced earlier regards the ongoing debate in the cognitive psychology community as to the presumed superiority of the power function over the exponential function for describing learning curves. Heathcote et al. (2000) conceded that the foregoing statement is true for aggregate data but claimed it is false for data analyzed at the individual level. However, the present data set, comprised of multiple parameter estimates derived from the individual data files of 140 participants, proved to be better fit by the two-parameter power function than the two-parameter exponential function in a post-hoc reexamination of the data. I speculated that this was the case because of the nature of the learning task. Practicing logic gates trio items invites interference to accumulate quickly, hindering performance and, resultantly, causing learning curves to flatten, as per the power function. If so, a circumstance in which interference was minimized should result in a more gradual learning curve, as per the exponential function.

To test the influence of rapidly accruing versus minimally occurring interference, a study similar to the present one could be designed that included a condition in which interference was not permitted to build to any significant degree. Using the same logic gates task as was used here, three groups could be compared that differed in the opportunity for PI and the timing of the PI release opportunities. The first group would experience no break in learning, just as the NoGap groups did in this experiment. This control group should demonstrate power law learning given the current findings. The second group would be comparable to the current Gap groups, but with one key difference. The gap activity would be neither CD nor NCD, per se, but would instead be a simple verbal task of the type used in the pilot experiment. Participants assigned to this group would engage in procedural practice of logic gates interrupted by a single block of a relatively simple but engaging verbal task between Blocks 8 and 9. The third, interference-minimizing group would experience a small gap between each block that involved solving 1/16 of the verbal gap task items. If my hypothesis that exponential and power function fits depend on PI, the third group's individual data would exhibit the shape of the more gradual, less asymptotic exponential function curve because performance would be less contaminated by interference effects. Perhaps even more intriguing to observe, however, would be the effects of the third group's steady learning pace on both transfer and long-term retention of the skill (see Carlson & Yaure, 1990).

Another direction for future research spawned by the present study would further investigate the lack of evidence of memory consolidation. A line of recent procedural learning research from the neuropsychological community (Hauptmann & Karni, 2002; Hauptmann, Reinhart, Brandt, & Karni, 2005) conceptualizes the construct I termed gap facilitation as delayed performance gains. Importantly, these gains are manifested only after the point in an individual's skill improvement—a different point for each person—at which asymptotic performance is observed. It is at this leveling-off, or saturation, point in the learning curve that memory consolidation processes are purportedly triggered which enable performance gains to continue to accrue over time even if practice ceases. Conversely, if practice ends prior to a subject's reaching his or her individually determined saturation point, no delayed learning gains would be expected. An in-depth analysis of individual attainment of asymptotic performance was neither hypothesized nor investigated in this experiment, but it could be fodder for future research.

Finally, despite the limitations acknowledged earlier, the research questions investigated here related to the impact of breaks in procedural practice of a cognitive skill could potentially influence cognitive skill acquisition theory because prominent models of learning do not predict skill improvement apart from practice. The findings could also contribute to memory literature by offering a rare investigation into the time-course of consolidation processes during a break in cognitive (as opposed to motor) skill learning over wakefulness (as opposed to over sleep).This line of research could potentially provide empirical evidence for utilizing strategically orchestrated breaks during periods of instruction. Unfortunately, regardless of instructional setting, there is little evidence at the present time that practitioners are devoting attention to the temporal spacing of learning (Pashler, Rohrer, & Cepeda, 2006). Thus, theoretical progress in this direction has potential application to the design of real-world skill training.

REFERENCES

Ackerman, P. L. (2011). 100 years without resting. In P. L. Ackerman (Ed.), *Cognitive fatigue: Multidisciplinary perspectives on current research and future applications* (pp. 11-43). Washington, DC: American Psychological Association.

Adams, J. A. (1955). A source of decrement in psychomotor performance. *Journal of Experimental Psychology, 49*(6), 390-394.

Adams, J. A. (1961). The second facet of forgetting: A review of warm-up decrement. *Psychological Bulletin, 58*, 257-273.

Adams, J. A., & Dijkstra, S. (1966). Short-term memory for motor responses. *Journal of Experimental Psychology, 71*(2), 314-318.

Alexandru, B. V., Robert, B, Viorel, L., & Vasile, B. (2009). Treating primary insomnia: A comparative study of self-help methods and progressive muscle relaxation. *Journal of Cognitive and Behavioral Psychotherapies, 9*(1), 67-82.

Ammons, R. B. (1947). Acquisition of motor skill: II. Rotary pursuit performance with continuous practice before and after a single rest. *Journal of Experimental Psychology,37*(5), 393-411.

Anderson, J. R. (1974). Retrieval of propositional information from long-term memory. *Cognitive Psychology, 6*, 451-474.

Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review, 89*, 369-406.

Anderson, J. R. (1983). *The architecture of cognition.* Cambridge, MA: Harvard University Press.

Anderson, J. R. (1993). *Rules of the mind.* Hillsdale, NJ: Lawrence Erlbaum Associates.

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. (2004). An integrated theory of the mind. *Psychological Review, 111*(4), 1036-1060.

Anderson, J. R., Fincham, J. M., & Douglass, S. (1999). Practice and retention: A unifying analysis. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25*(5), 1120-1136.

Anderson, J. R. & Schunn, C. D. (2000). Implications of the ACT-R learning theory: No magic bullets. In R. Glaser (Ed.), *Advances in instructional psychology: Educational design and cognitive science, 5,* (pp. 1-33). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Anderson, M. C., & Bjork, R. A. (1994). Mechanisms of inhibition in long-term memory. In D. Dagenbach & T. H. Carr (Eds.), *Inhibitory processes in attention, memory, and language* (pp. 265-325). San Diego, CA: Academic Press, Inc.

Anderson, M. C., & Neely, J. H. (1996). Interference and inhibition in memory retrieval. In E. L. Bjork & R. A. Bjork (Eds.), *Memory* (pp. 237-304). San Diego, CA: Academic Press.

Arai, T. (1912). *Mental fatigue (contributions to education, No. 54)*. New York, NY: Teachers College, Columbia University.

Ballard, P. B. (1913). Obliviscence and reminiscence. *British Journal of Psychology, 1*(II), 82.

Bartlett, F. (1958). *Thinking: An experimental and social study*. New York, NY: Basic Books.

Brady, B., & Stevens, L. (2000). Binaural-beat induced theta EEG activity and hypnotic susceptibility. American Journal of Clinical Hypnosis, 43(1), 53-69.

Buckner, R. L., Andrews-Hanna, J. R., & Schacter, D. L. (2008). The brain's default network: Anatomy, function, and relevance to disease. *Annals of the New York Academy of Sciences, 1124*, 1-38.

Buxton, C. E. (1943). The status of research in reminiscence. *Psychological Bulletin, 40*, 313-340.

Cameron, C. (1973). A theory of fatigue. *Ergonomics, 16*, 633-648.

Carlson, R. A., Khoo, B. H., Yaure, R. G., & Schneider, W. (1990). Acquisition of a problem-solving skill: Levels of organization and use of working memory. *Journal of Experimental Psychology: General, 119*(2), 193-214.

Carlson, R. A., & Shin, J. C. (1996). Practice schedules and subgoal instantiation in cascaded problem solving. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22*(1), 157-168.

Carlson, R. A., Sullivan, M. A., & Schneider, W. (1989). Practice and working memory effects in building procedural skill. *Journal of Experimental Psychology: Learning, Memory,and Cognition, 15*(3), 517-526.

Carlson, R. A., & Yaure, R. G. (1990). Practice schedules and the use of component skills in problem solving. *Journal of Experimental Psychology: Learning, Memory and Cognition, 16*(3), 484-496.

Carmichael, L., & Dearborn, W. F. (1947). *Reading and visual fatigue.* Cambridge, MA: Riverside Press.

Carr, M. F., Jadhav, S. P., & Frank, L. M. (2011). Hippocampal replay in the awake state: A potential substrate for memory consolidation and retrieval. *Nature Neuroscience, 14*(2), 147-153.

Cepeda, N. J., Pashler, H., Vul, E., Wixted, J. T., & Rohrer, D. (2006). Distributed practice in verbal recall tasks: A review and quantitative synthesis. *Psychological Bulletin, 132*(3), 354-380.

Cepeda, N. J., Vul, E., Rohrer, D., Wixted, J. T., & Pashler, H. (2008). Spacing effects in learning: A temporal ridgeline of optimal retention. *Psychological Science,19*(11), 1095-1102.

Chafin, S., Roy, M., Gerin, W., & Christenfeld, N. (2004). Music can facilitate blood pressure recovery from stress. *British Journal of Health Psychology, 9*, 393-403.

Davies, D. R., & Parasuraman, R. (1982). *The psychology of vigilance*. New York, NY: Academic Press.

Debarnot, U., Clerget, E., & Olivier, E. (2011). Role of the primary motor cortex in the early boost in performance following mental imagery training. *PLoS ONE, 6*(10), e26717.

Dempster, F. N. (1988). The spacing effect: A case study in the failure to apply the results of psychological research. *American Psychologist, 43*(8), 627-634.

Denny, M. R., Frisbey, N., & Weaver Jr., J. (1955). Rotary pursuit performance under alternate conditions of distributed and massed practice. *Journal of Experimental Psychology, 49*, 48-54.

Dewar, M., Alber, J., Butler, C., Cowan, N., & Della Sala, S. (2012). Brief wakeful resting boosts new memories over the long term. *Psychological Science, 23*(9), 955-960.

Dewar, M., Cowan, N., & Della Sala, S. (2007). Forgetting due to retroactive interference: A fusion of Muller and Pilzecker's (1900) early insights into everyday forgetting and recent research on anterograde amnesia. *Cortex, 43*(5), 616-634.

Dewar, M., Garcia, Y. F., Cowan, N., & Della Sala, S. (2009). Delaying interference enhances memory consolidation in amnesic patients. *Neuropsychology, 23*(5), 627-634.

Dinges, D. F., & Powell, J. W. (1985). Microcomputer analyses of performance on a portable, simple visual RT task during sustained operations. *Behavior Research Methods, Instruments, & Computers, 17,* 652–655.

Dudai, Y. (2012). The restless engram: Consolidations never end. *Annual Review of Neuroscience, 35,* 227-47.

Ebbinghaus, H. (1885/1964). *Memory: A contribution to experimental psychology* (H. A. Ruger, C. E. Bussenius, & E. R. Hilgard, Trans.). New York, NY: Dover. (Original work published 1885).

Eschrich, S., Munte, T. F., & Altenmuller, E. O. (2008). Unforgettable film music: The role of emotion in episodic long-term memory for music. *BMC Neuroscience, 9*(48), 1-7.

Estes, W. K. (1956). The problem of inference from curves based on group data. P*sychological Bulletin, 53*(2), 134-140.

Eysenck, H. J., & Frith, C. D. (1977). *Reminiscence, motivation, and personality: A case study in experimental psychology*. Oxford, England: Plenum.

Fitts, P. M. (1964). Perceptual-motor skill learning. In A. W. Melton (Ed.) *Categories of human learning* (pp. 243-285). New York, NY: Academic Press.

Fitts, P. M., & Posner, M. I. (1967). *Human performance.* Oxford, England: Brooks/Cole.

Gates, A. I. (1930). *Psychology for students of education (Rev. ed.).* Oxford, England: Macmillan.

Gilbert, S. J., Bird, G., Frith, C. D., & Burgess, P. W. (2012). Does "task difficulty" explain "task-induced deactivation?" *Frontiers in Psychology, 3*(125)*,* 1-12.

Gitomer, D.H. (1988). Individual differences in technical troubleshooting. *Human Performance, 1*(2), 111-131.

Gunzelmann, G., Moore, L. R., Gluck, K. A., Van Dongen, H. P. A., & Dinges, D. F. (2011). Generalizing mechanisms for time awake to time on task. In P. L. Ackerman (Ed.), *Cognitive fatigue: Multidisciplinary perspectives on current research and future applications* (pp. 83-101). Washington, DC: American Psychological Association.

Hauptmann, B., & Karni, A. (2002). From primed to learn: The saturation of repetition priming and the induction of long-term memory. *Cognitive Brain Research, 13*, 313-322.

Hauptmann, B., Reinhart, E., Brandt, S. A., & Karni, A. (2005). The predictive value of the leveling off of within-session performance for procedural memory consolidation. *Cognitive Brain Research, 24*,181-189.

Heathcote, A., Brown, S., & Mewhort, D. J. K. (2000). The power law repealed: The case for an exponential law of practice. *Psychonomic Bulletin & Review, 7*(2), 185-207.

Heuer, H., & Klein, W. (2003). One night of total sleep deprivation impairs implicit learning in the serial reaction task, but not the behavioral expression of knowledge. *Neuropsychology, 17*(3), 507-516.

Hintzman, D. L. (1974). Theoretical implications of the spacing effect. In R. L. Solso (Ed.), *Theories in Cognitive Psychology: The Loyola Symposium* (pp. 77-99). Potomac, MD: Lawrence Erlbaum Associates.

Hotermans, C., Peigneux, P., de Noordhout, A. M., Moonen, G., & Maquet, P. (2006). Early boost and slow consolidation in motor skill learning. *Learning & Memory, 13,* 580-583.

Hull, C. L. (1943). *Principles of behavior: An introduction to behavior theory.* Oxford, England: Appleton-Century.

Hull, C. L. (1951). *Essentials of behavior.* New Haven, CT: Yale University Press.

Huxtable, Z. L., White,M. H., & McCartor, M. A. (1946). A re-performance and re-interpretation of the Arai experiment in mental fatigue with three subjects. *Psychological Monographs, 59*(5), 1-52.

Jaeggi, S. M., Buschkuehl, M., Perrig, W. J., & Meier, B. (2010). The concurrent validity of the *N*-back task as a working memory measure. *Memory, 18*(4), 394-412.

Jancke, L., & Sandmann, P. (2010). Music listening while you learn: No influence of background music on verbal learning. *Behavioral and Brain Functions, 6*(3), 1-14.

Jenkins, J. G., & Dallenbach, K. M. (1924). Obliviscence during sleep and waking. *The American Journal of Psychology, 35*(4), 605-612.

Johnson, A. (2013). Procedural memory and skill acquisition. *Handbook of Psychology, 4*, 495- 520.

Kahneman, D. (1973). *Attention and effort*. Englewood Cliffs, NJ: Prentice-Hall.

Kane, M. J., Conway, A. R. A., Miura, T. K., & Colflesh, G. J. H. (2007). Working memory, attention control, and the *N*-Back task: A question of construct validity. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 33*(3), 615-622.

Kaneko, K., & Sakamoto, K. (2001). Spontaneous blinks as a criterion of visual fatigue during prolonged work on visual display terminals. *Perceptual and Motor Skills, 92,* 234–250.

Karni, A., & Sagi, D. (1993). The time course of learning a visual skill. *Nature, 365*(6443)*,* 250-252.

Kasprzak, C. (2011). Influence of binaural beats on EEG signal. *Acta Physica Polonica A, 119,* 986-990.

Kato, Y., Endo, H., & Kizuka, T. (2009). Mental fatigue and impaired response processes: Event-related brain potentials in a Go/NoGo task. *International Journal of Psychophysiology, 72,* 204-211.

Kimble, G. A. (1949). An experimental test of a two-factor theory of inhibition. *Journal of Experimental Psychology, 39,* 15-23.

Kimble, G. A., & Horenstein, B. R. (1948). Reminiscence in motor learning as a function of length of interpolated rest. *Journal of Experimental Psychology, 38*(3), 239-244.

Kirchner, W. K. (1958). Age differences in short-term retention of rapidly changing information. *Journal of Experimental Psychology, 55*(4), 352-358.

Kroll, N. E. A., Bee, J., & Gurski, G. (1973). Release of proactive interference as a result of changing presentation modality. *Journal of Experimental Psychology, 98*(1), 131-137.

Kyllonen, P. C. & Woltz, D. J. (1989). Role of cognitive factors in the acquisition of cognitive skills. In P. L. Ackerman, R. Kanfer, & R. Cudeck (Eds.), *Abilities, motivation, and methodology: The Minnesota Symposium on Learning and Individual Differences* (pp. 239-280). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Landauer, T. (1969). Reinforcement as consolidation. *Psychological Review, 76*(1), 82-96.

Lane, J. D., Kasian, S. J., Owens, J. E., & Marsh, G. R. (1998). Binaural auditory beats affect vigilance performance and mood. *Physiology & Behavior, 63*(2), 249-252.

Lavallee, C. F., Koren, S. A., & Persinger, M. A. (2011). A quantitative electroencephalographic study of meditation and binaural beat entrainment. *The Journal of Alternative and Complementary Medicine, 17*(4), 351-355.

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review, 95*(4), 492-527.

Logan, G. D. (1992). Shapes of reaction-time distributions and shapes of learning curves: A test of the instance theory of automaticity. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18*(5), 883-914.

Lorist, M. M., & Faber, L. G. (2011). Consideration of the influence of mental fatigue on controlled and automatic cognitive processes and related neuromodulatory effects. In P. L. Ackerman (Ed.), *Cognitive fatigue:Multidisciplinary perspectives on current research and future applications* (pp. 105-126). Washington, DC: American Psychological Association.

Lustig, C., & Hasher, L. (2001). Implicit memory is vulnerable to proactive interference. *Psychological Science, 12*(5), 408-412.

Marshall, L., & Born, J. (2007). The contribution of sleep to hippocampus-dependent memory consolidation. *Trends in Cognitive Sciences, 11*, 442-450.

McGeoch, J. A. (1932). Forgetting and the law of disuse. *Psychological Review, 39*(4), 352-370.

Melton, A. W. (September, 1969). *Repetition and remembering*. Paper presented as presidential address before Division of Experimental Psychology, meetings of the American Psychological Association, Washington, D. C.

Muellbacher, W., Ziemann, U., Wissel, J., Dang, N., Kofler, M., Facchini, S., Boroojerdi, B., Poewe, W., & Hallett, M. (2002). Early consolidation in human primary motor cortex. *Nature, 415,* 640-644.

Muller, G. E., & Pilzecker, A. (1900). Experimentelle Beitrage zur Lehre vom edachtniss. *Zeitschrift fur Psychologie, I*, 1-300.

Nairne, J. S., Neath, I., & Serra, M. (1997). Proactive interference plays a role in word-length effect. *Psychonomic Bulletin & Review, 4*(4), 541-545.

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of skill acquisition and the law of practice. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 1-55). Hillsdale, NJ: Erlbaum.

Newell, K. M. (1991). Motor skill acquisition. *Annual Review of Psychology, 42*, 213-237.

Owen, A. M., McMillan, K. M., Laird, A. R., & Bullmore, Ed (2005). *N*-back working memory paradigm: A meta-analysis of normative functional neuroimaging studies. *Human Brain Mapping, 25*(1), 46-59.

Padmanabhan, R., Hildreth, A. J., & Laws, D. (2005). A prospective, randomized, controlled study examining binaural beat audio and pre-operative anxiety in patients undergoing general anaesthesia for day case surgery. *Anaesthesia, 60*, 874-877.

Pashler, H., Rohrer, D., & Cepeda, N. J . (2006). How we learn: Temporal spacing and learning. *APS Observer*, *19*(3).

Peterson, L. R. (1966). Short-term verbal memory and learning. *Psychological Review, 73*(3), 193-207.

Peterson, L. R., & Peterson, M. J. (1959). Short-term retention of individual verbal items. *Journal of Experimental Psychology, 58*(3), 193-198.

Postman, L. (1969). Experimental analysis of learning to learn. *Psychology of Learning and Motivation, 3*, 249-297.

Postman, L., & Keppel, G. (1977). Conditions of cumulative proactive inhibition. *Journal of Experimental Psychology: General, 106*(4), 376-403.

Proctor, R. W., & Dutta, A. (1995). *Skill acquisition and human performance*. Thousand Oaks, CA: SAGE Publications, Inc.

Robertson, E. M., Pascual-Leone, A., & Miall, R. C. (2004). Current concepts in procedural consolidation. *Nature Reviews Neuroscience, 5*(7), 576-582.

Robertson, E. M., Pascual-Leone, A., & Press, D. Z. (2004). Awareness modifies the skill learning benefits of sleep. *Current Biology, 14*(3), 208-212.

Rosenbaum, D. A., Carlson, R. A., & Gilmore, R. O. (2001). Acquisition of intellectual and perceptual-motor skills. *Annual Review of Psychology, 52,* 453-470.

Rosenbloom, P. S. (Ed.), Laird, J. E. (Ed.), & Newell, A. (Ed.). (1993). *The Soar papers: Research on integrated intelligence, Vols. 1 & 2*. Cambridge, MA: The MIT Press.

Rosenbloom, P. S., & Newell, A. (1987). Learning by chunking: A production system model of practice. In D. Klahr, P. Langley, & R. Neches (Eds.), *Production system models and development* (pp. 221-286). Cambridge, MA: MIT Press.

Rubin, D. C., & Wenzel, A. E. (1996). One hundred years of forgetting: A quantitative description of retention. *Psychological Review, 103*(4), 734-760.

Scheufele, P. M. (2000). Effects of progressive relaxation and classical music on measurements of attention, relaxation, and stress responses. *Journal of Behavioral Medicine, 23*(2), 207- 228.

Schmidt, R. A. (1988). *Motor control and learning: A behavioral emphasis*. Champaign, IL: Human Kinetics.

Schneider, W., & Detweiler, M. (1987). Artificial intelligence and psychology project: A connectionist control architecture for working memory. *Department of Psychology,* Paper 417.

Schneider, W., Eschman, A., & Zuccolotto, A. (2002). E-Prime Psychological Software. Pittsburgh: Psychology Software Tools, Inc.

Schwarz, D. W. F., & Taylor, P. (2005). Human auditory steady state responses to binaural and monaural beats. *Clinical Neurophysiology, 116*, 658-668.

Sidman, M. (1952). A note on functional relations obtained from group data. *Psychological Bulletin, 49*(3), 263-269.

Singley, M. K., & Anderson, J. R. (1989). *The transfer of cognitive skill*. Cambridge, MA: Harvard University Press.

Stickgold, R. (2005). Sleep-dependent memory consolidation. *Nature, 437*, 1272-1278.

Thorndike, E. L. (1905). *The elements of psychology*. New York, NY: A G Seiler.

Underwood, B. J. (1945). The effect of successive interpolations on retroactive and proactive inhibition. *Psychological Monographs, 59*(3), 1-33.

Underwood, B. J. (1957). Interference and forgetting. *Psychological Review, 64*(1), 49-60.

Van Dongen, H. P. A., Maislin, G., Mullington, J. M., & Dinges, D. F. (2003). The cumulative cost of additional wakefulness: Dose–response effects on neurobehavioral functions and sleep physiology from chronic sleep restriction and total sleep deprivation. *Sleep, 26,* 117–126.

VanLehn, K. (1996). Cognitive skill acquisition. *Annual Review of Psychology, 47,* 513-539.

Wahbeh, H., Calabrese, C., Zwickey, H., & Zajdel, D. (2007). Binaural beat technology in humans: A pilot study to assess neuropsychologic, physiologic, and electroencephalographic effects. *The Journal of Alternative and Complementary Medicine, 13*(2), 199-206.

Walker, M. P. (2005). A refined model of sleep and the time course of memory formation. *Behavioral and Brain Sciences, 28*, 51-104.

Wechsler Adult Intelligence Scale (WAIS-III, 1997): PsychCorp division of Pearson Education, Inc.

Wickens, D. D., Born, D. G., & Allen, C. K. (1963). Proactive inhibition and item similarity in short-term memory. *Journal of Verbal Learning and Verbal Behavior, 2,* 440–445.

Wixted, J. T. (2004). The psychology and neuroscience of forgetting. *Annual Review of Psychology, 55*, 235-269.

Woltz, D. J., Gardner, M. K., & Bell, B. G. (2000). Negative transfer errors in sequential cognitive skills: Strong-but-wrong sequence application. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*(3), 601-625.

Woltz, D. J., Gardner, M. K., & Gyll, S. P. (2000). The role of attention processes in near transfer of cognitive skills. *Learning and Individual Differences, 12,* 209-251.